Essays on Mutual Funds and Fund Managers

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Abstract

This dissertation comprises of three chapters on mutual funds. **The first chapter** establishes the role of managers in the deceptive practice of window dressing. Employing comprehensive career history of U.S. mutual fund managers, I find strong jointly significant manager fixed effects, which are robust after addressing endogenous matching concerns. I use the connected sample instead of the classical movers sample to substantially enlarge the sample size and reduce the selection bias that long exists in the stream of literature. The estimated manager fixed effects are significant in making out-of-sample predictions. Further I establish that mutual fund interlocks through common managers are important channels that spread window dressing. **The second chapter** studies the investment strategies of mutual funds regarding their use of credit default swaps (CDS). Matches between mutual funds CDS positions and their underlying portfolio in the holdings facilitate a new approach in identifying CDS strategies that complements the macro level analyses in the existing literature. I find risk reducing incentives are dominated by speculative incentives, especially those to increase credit exposure via naked short CDS contracts. Experienced fund managers tend to take on more credit risk, while female managers are more likely to hedge comparing with their male peers. **The third chapter** employs the collapse of Lehman Brothers and the resulting sudden closures of CDS positions as a natural experiment to examine the risk and performance implications of mutual funds CDS investments. Funds on average load up on a significant amount of tail risk by trading CDS. While CDS users benefit when market conditions are favorable, they suffer during periods of clustered defaults. Funds forced to resolve their Lehman CDS contracts exhibit persistent inferior performance in the post-crisis period comparing

with their matched peers.

Keywords: Mutual Fund; Window Dressing; Manager Fixed Effects; Social Network; Credit Default Swap; Lehman Brothers; Fund Performance; Tail Risk

Zusammenfassung

Die vorliegende Dissertation besteht aus drei Kapiteln über die Investmentfonds. **Das erste Kapitel** befasst sich mit der Rolle der Fondsmanager in der Bilanzverschönerung. Auf Basis der Analyse der Karrierewege von amerikanischen Fondsmanagern werden signifikante zusammenwirkende Manager-Fixed-Effects identifiziert, die nach der Kontrolle der endogenen Matching-Probleme immer noch robust sind. In dieser Studie wird eine zusammenhängende Stichprobe statt der klassischen gebildet, um den Stichprobenumfang zu vergröern und die in der vorangegangenen Literatur existierende Auswahlverzerrung zu reduzieren. Die geschätzten Manager-Fixed-Effects haben signifikante Einflüsse auf die Out-of-Sample-Vorhersagen. Auerdem wird festgestellt, dass die Verriegelungen der Investmentfonds, die von gemeinsamen Managern verwaltet wurden, wichtige Kanäle für die Bilanzverschönerung verursachen. **Das zweite Kapitel** beschäftigt sich mit den Investmentstrategien der Fonds im Hinblick auf die Nutzung von Credit Default Swaps (CDS). Die Zuordnung der CDS-Positionen der Investmentfonds zu ihrem Bestandportfolio bietet eine neue Methodik zur Identifizierung der CDS-Strategien und kompensiert somit die Analysen der existierenden Literatur auf der Makroebene. Die Ergebnisse zeigen, dass die Anreize zur Risikoreduzierung die Spekulationsanreize dominieren, insbesondere, wenn die Kreditexposition durch ungedeckte Leerverkäufe der CDS-Verträge erhöht wird. Die erfahrenen Fondsmanager tendieren dazu, mehr Kreditrisiko in Kauf zu nehmen, während es für die Fondsmanagerinnen wahrscheinlicher als für ihre männlichen Kollegen ist, gegen das bestehende Risiko abzusichern. **Der letzte Teil** nimmt die Pleite von Lehman Brothers unter die Lupe, um sich mit der daraus resultierenden unerwarteten Schlieung der CDS-Positionen als einem natürlichen Experiment auseinanderzusetzten. Diese Studie dient zur Untersuchung der Risiko- und Leistungsimplikationen der CDS-Investments der Fonds. Die Investmentfonds besitzen bei ihren CDS-Transaktionen im Durchschnitt einen beachtlichen Teil Extremrisiko. Während die CDS-Nutzer von guten Gesamtmarktlagen profitieren, erleiden sie unter Verlusten bei geclusterten Ausfällen. Insofern sind diejenigen Fonds, die ihre Lehman CDS-Verträge zwangsläufig auflösen mussten, durch eine permanente schlechte Fondsperformance in der Nachkrisenzeit gekennzeichnet im Vergleich zu ihren Konkurrenten.

Stichwörter: Investmentfond; Bilanzverschönerung; Manager-Fixed-Effect; Sozialnetzwerk; Credit Default Swap; Lehman Brothers; Fondsperformance; Extremrisiko

Outline

The dissertation consists of three self-contained chapters on mutual funds.

Chapter 1: Window Dressing Contagion through Interlocked Fund Management Teams

The first chapter studies the manager fixed effects in mutual fund's controversial practice of window dressing. The research question is motivated by observing the fair amount of manager turnover within the mutual fund industry, the intensive interconnection among funds through managers, and the quasi-legal nature of the window dressing practice. I employ a comprehensive date set on the manager career history of all U.S. equity fund managers to establish that manager effects, in terms of both Bertrand and Schoar (2002) type of manager fixed effects and Abowd, Kramarz and Margolis (1999) manager fixed effects, are significant in explaining window dressing. The first method relies on manager turnover to estimate manager fixed effects with the presence of fund fixed effects, while the second greatly enlarges the sample from the movers to the connected. The switch of the method improves the estimation power, and at the same time partially addresses the concern that the Bertrand and Schoar (2002) estimation is biased towards movers. There are certainly endogeneity concerns, for which I tackle with a number of robustness tests. The estimated manager fixed effects are significant in making out-of-sample predictions. Further, by matching funds according to their manager links, I establish fund interlocks through common managers spread window dressing in the sense that a fund is more likely to window dress if its interlocked fund has previously window dressed.

Chapter 2: Mutual Fund CDS Strategies

The second chapter and the third chapter deal with the derivative use of fixed-income funds. The focus of chapter 2 is to classify and document CDS strategies of fixed-income funds and to take a trial on analyzing cross-fund-within-family CDS strategies. For the first time I reveal mutual fund CDS strategies on transaction level by matching U.S. fixed income mutual fund's Credit Default Swap (CDS) holdings collected from SEC filings with their reported portfolio holdings from Morningstar. Previous literature either makes informed predictions based on aggregate CDS and bond market data, or does not have the match between CDS and their underlying. Therefore it was impossible to inspect the CDS trades in terms of the intended strategies. CDS strategies are classified to one of the five categories: negative basis trading, hedging, bond synthesizing and speculating via naked long or short CDS positions. Risk reducing incentives are dominated by speculative incentives, especially those to increase credit exposure via naked short CDS contracts. I additionally check the fund and manager characteristics that are correlated with each of the strategies. I confirm the existence of cross-fund-within-family trades facilitated by CDS by matching naked CDS positions with the portfolio bond holdings of other funds in the family. Between the two hypotheses that explain the cross-fund trades, I find supportive evidence for the family level strategic concerns.

Chapter 3: Tail Risk, Fund Performance and Credit Derivatives Trading: Evidence from the Lehman Collapse

The aim of the third chapter is to assess the risk and performance implications of CDS trades. In addition, I analyze the universe of U.S. bond funds' CDS holdings which is the most comprehensive data set to date. A natural challenge of the research is the endogeneity concerns. Apart from concurrent events and other missing factors that prevent one from establishing causal relationships, the reverse causality that funds may opt to trade CDS in anticipation of future risk and return profiles is also a valid concern. We reduce the level of endogeneity in this problem by the identification that utilizing the collapse of Lehman Brothers as well as the resulting sudden closure of mutual fund's CDS holdings with Lehman as the counterparty as a natural experiment. Treated funds are defined as those with sufficient Lehman CDS exposures. Control funds are propensity score matched funds with similar pre-event characteristics as the treated funds but without Lehman exposure. CDS users perform well outside of the crisis periods, but suffer from significant losses during the crisis, which suggests they are taking on excessive credit risks. Both difference-in-differences (DiD) and event study methods are used to establish that the sudden drop of CDS positions of the treated introduces lower annualized 5-factors alpha for these funds comparing with their matched peers post crisis.

Chapter 1

Window Dressing Contagion through Interlocked Fund Management Teams

Abstract

Employing the comprehensive career history of U.S. mutual fund managers, we analyze the effect of heterogeneous and idiosyncratic manager style on mutual fund's deceptive practice of window dressing. We find strong jointly significant manager fixed effects, which are robust after addressing endogenous matching concerns. We use the connected sample method instead of the classical movers sample method to greatly enlarge the sample size and reduce the selection bias that long exists in the stream of literature. The estimated manager fixed effects are strong in making out-of-sample predictions on window dressing. We establish that mutual fund interlocks through common managers are important channels that spread window dressing.

Keywords: Mutual Fund, Window Dressing, Manager Fixed Effects, AKM Method, Social Network

JEL classification: G11, G23, G28, G41

1.1 Introduction

As per the requirement of the U.S. Securities and Exchange Commission, the SEC, all mutual funds fall into the justification of the Investment Company Act of 1940 have to report their portfolio holdings periodically[1]. The practice of window dressing emerges as mutual funds alter their holdings towards reporting period end in order to record their manipulated compositions. Window dressing has long been noticed by both the regulators and the market participants. For example, Paul Roye, the director of the SEC's investment management division, made several public speeches during the 2000-2001 period that mentioned how the SEC had always kept an eye on window dressers in the mutual fund industry.

We also are concerned about the misleading practice known as "window dressing"...OCIE is examining trading patterns to detect violations in this area. We view this as an anti-fraud violation. Investors are misled if they are told that the fund is investing consistent with prospectus disclosure when it is not. —Paul F. Roye, Director, Division of Investment Management U.S. Securities & Exchange Commission[2]

Not only did the SEC concern about the behavior, they filed cases against window dressers in 2005. Although it is usually very difficult to prove that the funds intentionally misled investors, the SEC manage to do that in the following case:

The Securities and Exchange Commission ("Commission") announced that on April

[1]The holding reports have to be filed semi-annually before 2004 in NCSR and NCSRS reports and afterwards quarterly in NQ as well as the above mentioned annual and semi-annual reports

[2]Speech by SEC Staff: The Exciting World of Investment Company Regulation [`https://www.sec.gov/news/speech/spch500.htm`, visited on 27.08.2015], see also [`https://www.sec.gov/news/speech/spch412.htm`] and [`https://www.sec.gov/news/speech/spch438.htm`] for the other SEC staff speeches concerning window dressing.

6, 2005, it filed a civil action in the United States District Court for the Western District of Pennsylvania against...In particular, ... In order to conceal the effect of their trading, which otherwise would have been disclosed in monthly account statements, ... sold the unauthorized positions before month-end, and repurchased them shortly thereafter. This strategy of "window dressing" prevented clients from discovering the scheme.[3]

We need to make a clear distinction among portfolio re-balancing, window dressing and portfolio pumping. There is nothing illegal for mutual funds to trade just before the reporting period ends per se, it is the motivation and consequences of such actions that complicate their legal implications. Window dressing is of deceptive nature. Mutual funds window dress in order to hide their held portfolio during the reporting periods, such that they can charm investors, attract inflows or obey their investment objectives. If such manipulations further pumped stock prices towards the direction in favor of funds, then they are manipulating stock prices and conducting the illegal practice of portfolio pumping.

Starting from documenting the turn-of-the-year effect, evidences of window dressing have long been discussed. While the turn-of-the-year effect is not the focus of this paper, the abnormal returns generated by small cap stocks around year ends have been documented in the early literature, for example Rozeff and Kinney (1976) and Roll (1983). Two common explanations of this phenomenon are tax-loss-selling and window dressing incentives. Although there is no general consensus regarding which of the two incentives best explain the turn-of-the-year effect, window dressing motive is present even in the papers that claim tax-loss-selling is the more important attribute[4]. Lakonishok, Shleifer, Thaler and Vishny (1991) notice US pension funds disproportionately sell poorly performed stocks, especially towards year ends. In a comprehensive paper on window dressing Agarwal,

[3]SEC Litigation No.19170 [`https://www.sec.gov/litigation/litreleases/lr19170.htm`, visited on 27.08.2015]

[4]See for example Lakonishok, Shleifer, Thaler and Vishny (1991), Sias and Starks (1997), O'Neal (2001), Meier, Schaumburg et al. (2004) and Sikes (2014) for mixed evidences.

Gay and Ling (2014) propose a rationale such that window dressing may exist with the presence of rational investors. Yet we still need to bridge the gap between the window dressing literature and the manager fixed effects literature to exam the role of mutual fund managers in window dressing. Given the private and quasi-legal nature of window dressing, it is highly unlikely the practice is originated independently in each fund. Thus looking at managers' role may help us understand the mechanism whereby the practice is transmitted among funds, and will have policy implications afterwards.

The purpose of this article is to provide evidences that managers do play a role in window dressing and the fund interlocks through common manager contribute to the spreading of the practice.

Employing the classical method of Bertrand and Schoar (2002) to detect manager fixed effects with the presence of fund fixed effects as the first step, we find strong evidence that managers are related to funds' decisions to window dress. The F statistics for joint significance are high, suggesting an important role of managers.

Getting beyond the sample of funds with manager turnover, which is the key of identification in Bertrand and Schoar (2002) and other papers with similar methodology, we also confirm the results with a Abowd, Kramarz and Margolis (1999) structured sample. The new method significantly enlarges the sample from the movers sample to the connected sample. All managers, movers or not, who work for funds that have at least one manager moving to other funds will be included in the sample. The estimations are more powerful with the connected sample. And more importantly, this partially addresses the selection bias concern of Bertrand and Schoar (2002), which is criticized for not taking care of the potential fundamental differences between movers and non-movers.

Mutual funds and managers are endogenously matched such that it is possible mutual funds intentionally hire managers with certain characteristics just in order to window dress. If this is the case, the observed manager effects would rather be fund effects. We partially address this endogenous matching issue with a propensity score matched sample as well as a number of robustness checks.

We conduct several sub-sample tests and get statistically similar results. We confirm that even for those bottom 20% performing managers, they also play an role in window dressing. It is very unlikely that mutual funds hire those bad performers in order to window dress. We continue to address this issue with placebo tests, in which we find distortions in manager-fund matches significantly reduce the manager fixed effects detected, indicating managers lead the changes instead of the opposite. Because if firms hire managers to window dress, they should have already started before managers join thus stronger manager fixed effects should be detected.

In addition, we test whether fund governance affects managers' decisions to window dress and find that even in restricted funds, managers' justifications are also important. The manager fixed effects we find are not just proxies for fund governance. The complicated structure of management teams may bias the results against us, so that the detected manager fixed effects could be the lower bounds. We check the sample of single manager funds and indeed find more significant results in favor of our hypothesis. Single managers matter even more in making funds' decisions to window dress.

We find the estimated manager fixed effects can make powerful out-of-sample predictions. Identified window dressers tend to significantly increase funds' probability to start window dress, even out of the sample that defined those managers as pro window dressing.

To the extent that managers' "fixed effects" may vary over time, then our previous analyses will underestimate the importance of managers in window dressing. We take a different approach and find fund interlocks by common managers significantly explain funds' initiation of window dressing, suggesting a potential mechanism of how window dressing spread across funds.

In order to open the black box of the estimated manager fixed effects, in Appendix A we exam in detail which manager attributes are among the important factors in these fixed effects. In particular we investigate whether managers' career networks play a role in their window dressing behaviour. We find managers with higher number of Linkedin connections are likely to window dress. We provide several explanations to address this issue. We additionally check if manager education, tenure and career development contribute to the manager fixed effects. The Agarwal, Gay and Ling (2014) paper argues a mutual fund is making a risky bet on its performance during the reporting delay period when it decides to window dress, and the practice itself, e.g. holding winning stocks, serves as a signal to the market. We hypothesize if the managers decide to send signals to market participants in quarterly reports, they may try to signal the market through other channels as well, for example their personal education. We cannot find strong evidence to support this view.

This article makes several contributions to the existing literature in term of window dressing, spreading of negative practices and more broadly managerial behavior. First of all, to the best of our knowledge this is the first paper that looks at the relationship between manager characteristics and window dressing. Existing literature explains window dressing by fund characteristics including alpha, size, turnover ratio, expense ratio, trading activeness...etc. This is certainly not the whole picture. Patel and Sarkissian (2013) is the only paper we find that looks at window dressing and managerial structure, but they are only concerned with the team versus single manager implications. Second, inspired by Bizjak, Lemmon and Whitby (2009), we provide evidences on how common managers and fund interlocks can contribute to the spreading of window dressing. The spreading of negative practices is generally more eye-catching in the finance literature and particularly interesting for regulators. Better understanding in this regard helps to shape policy that better incentivize managers, enforce accurate reporting, improve transparency and protect investor rights. Third, we take a further step on the literature of manager fixed effects by asking which specific manager characteristics constitute the estimated manager fixed effects. Fourth, we follow the debate on whether managers have skills. Since the seminal paper of Bertrand and Schoar (2002), numerous papers find managers matter in various corporate policies. However, the stream of literature is attacked for the following reasons. For one thing, the matches between managers and funds are certainly not exogenous. In a paper directly addressed to the Bertrand and Schoar (2002) paper, Fee, Hadlock and Pierce (2013) find that firm policy changes are not significantly related to CEO exogenous departures. We try to address this endogeneity issue in the analysis. For another thing, the sample restriction of Bertrand and Schoar (2002) casts doubt on the power of the tests, we extend the sample selection following Abowd, Kramarz and Margolis (1999) and several other very limited number of papers in finance thereby increasing the generality of the results. While we are not aiming at tackling the big question of whether managerial behaviors matter, our study does shed light on this broad issue from a special perspective.

The rest of the article is organized as follows: Section 2 gives a brief overview of related literature on window dressing and managerial style, from which we derive our testable hypotheses. Section 3 details our data sources, sample selection process and some brief summary statistics. In Section 4 we exam the manager fixed effects and check whether managers matter in funds' decisions to window dress. We also conduct several robustness checks to address the potential endogeneity concerns. In Section 5 we take a different perspective and check how the level of interlocks affects the spreading. Section 6 concludes. Furthermore, a discussion on which specific manager characteristics contribute to the displayed manager fixed effects is given in Appendix A.

1.2 Related Literature and Hypothesis Developmen-t

1.2.1 Managerial Behavior and Firm Policy

Classical researches on window dressing implicitly assume no role of managers, or managers are homogenous and selfless, as is usually assumed by neoclassical economics models. However, this is counter-intuitive. It is an empirical question whether managers have discretion in corporate decision making. In an early influential paper Murphy and Zimmerman (1993) study financial policy making surrounding CEO departures and find no strong evidence that manager discretion matters. Instead, the poor performance of firms before CEO departures seems to drive the updating of policies.

The seminal paper of Bertrand and Schoar (2002) opens a whole new area of exploring managerial behavior. The most important methodological contribution of the work is showing how to separately examine the effects of managers and firms on firm policies. When firm fixed effects are controlled for, detection of manager fixed effects is possible when there is manager turnover. They find managers are with style in shaping firms' spending, acquisition, leverage, dividend policies...etc. Following the paper, a series of papers study various other firm policies and generally find supporting evidences that managers do have discretion and style in the decisions.[5]

Bertrand and Schoar (2002) make several assumptions and one of the most important

[5]See for example Adams, Almeida and Ferreira (2005), Frank and Goyal (2007) and Graham, Li and Qiu (2012)

is that the inherent manager style does not change overtime, nor does it change across different employers. Apart from this, they acknowledge that they have no say on which manager characteristics are related to the effects they observe, and on whether there are casual relationships. These problems are rooted from the agency models which either 1. assume managers do have discretion, but their idiosyncratic management styles are limited by the heterogenous levels of firm governance; 2. managers differ by their match quality with firms, so that the idiosyncratic management styles exhibited are purposefully chosen by firms[6]; or 3. market conditions drive corporate decision making as well as hiring decisions, so that management styles are nothing but projections of economic environments.

In order to address the problem of endogenous matching, Cronqvist and Fahlenbrach (2009) randomly allocate block-holders' ownership stake into two subsets, and assume in one of the subsets block-holders acquire their stake one or two years before the actual transaction date. Comparing the block-holder fixed effects estimated from the hypothetical sample and the actual sample, no conclusive evidence can be found regarding the correlation between the two sets of fixed effects. The authors interpret it as suggesting firms do not seem to seek out target block-holders in order to change certain firm policies. Fee, Hadlock and Pierce (2013) tackle the problem using exogenous CEO departures, and find no significant firm policy changes following the departures. In contrast, they do detect policy variations after endogenous CEO departures. Their results suggest managers are selected in order to execute firms' intentions.

Acknowledging the difficulties to deal with endogenous matching, Pool, Stoffman, Yonker and Zhang (2014) take a different perspective and check how shocks to mutual

[6]There are a fair amount of empirical studies that examine mutual fund manager turnover, see for example Khorana (1996) on top mutual fund management turnover, Chevalier and Ellison (1998) on different career concerns of mutual fund managers, Kostovetsky (2007), Nohel, Wang and Zheng (2010) and Deuskar, Pollet, Wang and Zheng (2011) on human capital movement between mutual funds and hedge funds and their side by side management.

fund managers' personal wealth affect their risk taking behavior in portfolio investments. More specifically they document a both statistically significant and economically meaningful decrease in the risks of the funds when those managers' home values substantially declined.

1.2.2 Window Dressing

The primary focus of our paper though, is not trying to engage in the big discussion of whether managers matter. We aim to provide first evidence on how window dressing is transmitted across funds through common managers and fund interlocks. The finance literature realizes the so-called turn-of-the-year effect before documenting window dressing. Window dressing is proposed in for example Lakonishok, Shleifer, Thaler and Vishny (1991) to explain the effect, alongside the alternative hypothesis of tax-loss-selling. Replacing the buy and sell intensity, Kacperczyk, Sialm and Zheng (2008) come up with a measure to quantify window dressing, the backward holding return gap (BHRG). Assuming the reported portfolio holdings have been held for the entire period between current report date and prior report date, the gap between the implied return and the actual return of funds serves as a proxy of window dressing. Agarwal, Gay and Ling (2014) conduct a determinants study of window dressing and establish that fund performance, size, turnover ratio and trade cost are correlated with BHRG. They run intraquarter and December tests to confirm that the detected window dressing is not just momentum trading. More importantly, they establish the existence of window dressing with rational investors. There can be an up to 60 days delay when funds file reports, thus window dressing is comparable to a risky bet. If the fund performances of window dressers during the delay period are good, then investors may perceive the manipulated favorable reports as genuine reflections of manager skills; while if the fund performances during the delay period are bad, then funds lose the bet and investors realize the reports are misleading.

1.2.3 Hypotheses

There are at least three reasons we believe why window dressing could be a manager matter, in addition to a fund matter. To begin with, as is argued by Bizjak, Lemmon and Whitby (2009), this is a negative and private practice. Given its nature it is very unlikely that managers acquires the knowledge regarding window dressing through public channels especially in early years. In this regard, when managers travel from one fund to another, they will most likely carry their knowledge on window dressing with them, consider the possibility of window dressing when making investment decisions before reporting period ends, and share the knowledge with their colleagues in the management team. Second, window dressing is not easy to implement. Being on the edge of legal and illegal, managers have to possess skills in order to hide their true intention while at the same time avoid pumping up stock prices.[7] Third, numerous studies establish that managers do have styles even after accounting for possible endogeneity. Our first testable hypothesis is:

Hypothesis I: Idiosyncratic manager style matters for window dressing. In particular, managers' willingness to connect positively contribute to window dressing.

We explore further the mechanism window dressing is spreading across funds. In the literature on firms' board connectivity, for example Davis (1991) and Bizjak, Lemmon and Whitby (2009), scholars find a number of corporate practices, for example poison pills and option backdating, spread across firms through board connections. Not only does board connectivity matter, but its influence is stronger with tighter interlocks. For

[7] We do not believe it is the trading desk who possesses the skill, because in the end managers will decide which stocks to trade.

any fund periods in the sample, we define the level of interlocks between fund i at time t with fund j at time k as:

$$\Lambda_{(it)(jk)} = \frac{\frac{CN_{(it)(jk)}}{N_{it}} + \frac{CN_{(it)(jk)}}{N_{jk}}}{t - k + 1} \tag{1.1}$$

Where Λ is the interlock measure, N is the number of managers of each fund period, and CN is the number of common managers for the fund-period pair. Notice we require $t \geq k$. The measure is normalized by dividing its standard deviation after subtracting the mean. We formulate hypothesis 2 as follows:

Hypothesis II: Inherent manager styles help explaining the spread of window dressing across funds. A fund's probability to start window dress is higher when there is a pro window dressing manager joining. Further, the closer the interlock between fund periods, the higher the probability that a fund starts to window dress conditional on the matched fund is a window dressing fund.

1.3 Data and Sample Construction

The primary data source of this research is Morningstar Direct, from which we extract the complete history of manager career for all U.S. equity funds. We keep only open end equity funds following previous literature, but keep the passively managed funds as well. Passively managed funds are usually excluded in previous mutual fund studies but in our case even they can engage in window dressing. Considering it is even harder for passively managed funds to over perform their benchmarks, they may as well have the incentive to window dress[8].

[8]For example, they could temporarily deviate from their investment objectives, and window dress just before reporting period ends in order to comply with the regulations.

We keep Morningstar fund ID as the primary fund identifier. We keep only data from September 1998 due to data limitations in CRSP Survivorship Bias Free Mutual Fund Database from which we get the fund level data. We drop managers that appear only once in the sample as they are difficult to interpret especially given the sizes of mutual fund management teams. The match between the Morningstar and CRSP databases is completed through tickers and CUSIPs. We follow the common practice to deal with multiple share classes in CRSP, so that fund size is the aggregate TNA across all share classes and other variables like fund return are TNA-weighted average values.

In order to compute the backward holding return, we acquire mutual fund holdings from Thomson-Reuters Mutual Fund Database. MFlinks provides the match between the Thomson database and CRSP Survivorship Bias Free Mutual Fund Database. Here we use Rdate as the effective date of reports. Additionally we need stock price series from CRSP and merge them with the holding database to get implied fund returns. The implied backward holding returns are computed by the adjusted holding stock returns during the period weighted by stock values, where stock values are number of shares times raw stock prices at the beginning of each period. Then the backward holding return gap, our primary measure for window dressing[9], would be:

$$\text{BHRG} = \text{Implied backward holding return} - (\text{Actual fund return} + \text{Fund expense ratio}) \tag{1.2}$$

We proxy fund governance by the number of restrictions they face as reported in N-SAR filings.[10] We follow Almazan, Brown, Carlson and Chapman (2004) and use funds' leverage, derivative trading and illiquid asset holding restrictions to come up with an aggregate measure of fund restrictions for each fund period.

[9]We also use rank gap in the manager fixed effects analyses and find very similar results. For the rest of the paper we keep BHRG as the major measure for window dressing.

[10]We thank Laurenz Klipper for generously providing us the data.

Our final sample comprises of 3976 managers, 1566 U.S. open end equity funds and 9346 unique manager-fund combinations. Our panel variable, unless stated otherwise, is manager-fund pairs. So that the data is structured on manager(fund)-time level. In Table 1.1 we summarize the big picture of manager-fund matches.

[Table 1.1 about here.]

We see from panels A and B that roughly half of the managers (49.6%) in the sample appear only once during their entire career within our sample period[11]. These managers are stayers. The movers, who are critical for the identification strategy, account for the other half. The benefit of Abowd, Kramarz and Margolis (1999)'s model is examined in panel C. More than half of the funds have more than 50 movers, this significantly enlarges the sample that we can use to identify manager fixed effects, while only 86 funds have never had one mover during the sample period. We visualize such mutual fund connections in Figure 1.1.

[Figure 1.1 about here.]

Funds and fund families are intensively connected by moving managers. A large number of managers switch jobs even across fund families. It is therefore interesting to check whether managers carry their styles during such switches, and how do fund interconnections facilitated by managers shape fund decisions.

[11]It does not necessarily imply that half of the present day fund managers worked for one fund since managers may drop out of the sample if they move to other industries.

1.4 Manager Fixed Effects

1.4.1 The Classical Approach

We quantify manager fixed effects first with the presence of fund fixed effects. Notice when there is no manager turnover, manager fixed effects and fund fixed effects would be perfectly collinear. Our baseline specification is:

$$y_{(ij)t} = \beta x_{it} + \delta_t + \alpha_i + \gamma_j + \epsilon_{(ij)t} \tag{1.3}$$

Where $y_{(ij)t}$ are the window dressing measures for the ij's fund-manager pair, x_{it} are fund level control variables, δ are time fixed effects, α are fund fixed effects, and γ are manager fixed effects[12].

Applying the empirical framework that is similar to Bertrand and Schoar (2002), we report manager fixed effects in Table 1.2. Notice since a fund can have multiple managers, and a manager can work for multiple funds at the same time, the regressions will be multi-dimensional as opposed to Bertrand and Schoar (2002).

[Table 1.2 about here.]

We estimate the baseline regression in panel A. Each row represents a regression. All coefficients and significance levels of control variables are not reported here as at the moment we are concerned with the joint significance of manager fixed effects. The F statistics is 7.05 with the high level of degrees of freedom, rejecting the null that manager fixed effects are not jointly significant. Further when comparing the adjusted R squared between row 1 and row 2, we find adding the almost 4000 manager dummies slightly increases the power of the regression. The increase may seem minimum but this

[12]In unreported analysis, we first replicate the analysis of Agarwal, Gay and Ling (2014) on the determinants of window dressing, without manager fixed effects, in order to make sure that our sample is consistent with previous studies. Our results are similar to those of Agarwal, Gay and Ling (2014) in terms of both statistical significance and economic magnitude.

R squared is adjusted for the number of explanatory variables. We find similar patterns when replacing the dependent variable by BHRG 10%, a dummy variable that equals to one if the BHRG is among the top 10% across all funds for the period.

Recall we have multi-dimensional regressions, and this potentially can be a problem if there is a cluster of manager turnover as teams moving all together. It does not change our results regarding the importance of manager fixed effects but does change the interpretation. Also for funds with a large management team, it is difficult to judge and rationalize the observed manager fixed effects. We restrict the sample to funds with a single manager in panel D so that we can have a cleaner set up. Similar message reveals, with an even higher F statistic.

A major critic to the empirical setting above is it cannot rule out the possibility of endogenous matching, so that funds may seek managers with window dressing style or skill in order to start window dressing themselves. While we will further address this important issue later in Section 1.4.4, we tackle this problem by a sub-sample analysis in panel C that considers only the bottom 20% performing managers. It is very unlikely that mutual funds hire those bad performers in order to window dress. The F statistic is 3.54, which is still significant. We are not ambitious to claim the endogenous matching story is ruled out as a proper identification strategy will be needed to make that claim.

In addition, for the sub-sample tests of restricted funds in panel B, manager fixed effects still explain variation in BHRG. Thus it is unlikely that the observed manager styles are just proxies of fund governance. Given the vast existence of manager fixed effects, there is no good reason to believe those idiosyncratic manager style would disappear with tight fund governance, rather than being compressed. We also rule out the possibility that more restricted funds and managers with less style are better matches so that those funds intentionally hire low window dressing probability managers.

1.4.2 The AKM Approach

Now we move from the Bertrand and Schoar (2002) set up to the AKM set up. Start from our baseline specification[13]:

$$y_{(ij)t} = \beta x_{it} + \delta_t + \alpha_i + \gamma_j + \epsilon_{(ij)t} \tag{1.4}$$

Denote F_{ijt} as a dummy that equals to one if manager j works for fund i at time t, and zero otherwise, equation 1.4 can be rewritten as:

$$y_{ijt} = \beta x_{it} + \delta_t + \sum_{i=1}^{I} F_{ijt}\alpha_i + \gamma_j + \epsilon_{ijt} \tag{1.5}$$

Now take the average over t and i for each manager j to get:

$$\bar{y}_j = \beta \bar{x}_j + \bar{\delta}_t + \sum_{i=1}^{I} \bar{F}_{ij}\alpha_i + \gamma_j + \bar{\epsilon}_j \tag{1.6}$$

Now we can eliminate the manager fixed effects by within transformation:

$$y_{ijt} - \bar{y}_j = \beta(x_{it} - \bar{x}_j) + (\delta_t - \bar{\delta}_t) + \sum_{i=1}^{I}(F_{ijt} - \bar{F}_{ij})\alpha_i + (\epsilon_{ijt} - \bar{\epsilon}_j) \tag{1.7}$$

Fund fixed effects are now identified using managers that move ($F_{ijt} - \bar{F}_{ij} \neq 0$). Now recover manager fixed effects after estimated the above α and β:

$$\hat{\gamma}_j = \bar{y}_j - \hat{\beta}\bar{x}_j - \sum_{i=1}^{I} \bar{F}_{ij}\hat{\alpha}_i \tag{1.8}$$

[13] The discussion on the methodology of AKM method follows from Graham, Li and Qiu (2012) and Ewens and Rhodes-Kropf (2015).

As long as a fund has one mover, fund fixed effects can be estimated thus all managers in that fund, both movers and stayers, would have manager fixed effects recovered. The Bertrand and Schoar (2002) specification puts firm and CEO dummies into the regression and estimate them all together. Thus only movers are included in estimating whether CEO effects can explain cross sectional variation in corporate policy variables. Here the AKM method extends the sample from the "mobility" sample to "connected" sample. Abowd, Kramarz and Margolis (1999) formally prove that connectedness is necessary and sufficient condition for the separate identification of person and firm fixed effects. There are at least 3 advantages employing the AKM method: First of all, it partly addresses selection bias. Since we do not know if there are systematic differences between movers and non-movers, estimation results based on the movers sample may introduce a selection bias. By enlarging the sample to include a significant portion of non-movers, this bias is reduced. Second, the larger sample size provides more estimation power. Third, there exists a more efficient computing algorithm since the regression we are estimating has a design matrix that is only a fraction of the original in terms of dimension[14].

In addition to the joint significance levels of manager fixed effects, we also decompose the model sum of squares to check the fraction that can be attribute to manager fixed effects following Graham, Li and Qiu (2012):

$$\begin{aligned} R^2 = \frac{cov(y_{ijt}, \hat{y}_{ijt})}{var(y_{ijt})} &= \frac{cov(y_{ijt}, \hat{\beta}_{ijt}x_{it} + \hat{\delta}_t + \hat{\alpha}_i + \hat{\gamma}_j)}{var(y_{ijt})} \\ &= \frac{cov(y_{ijt}, \hat{\beta}_{ijt}x_{it} + \hat{\delta}_t)}{var(y_{ijt})} + \frac{cov(y_{ijt}, \hat{\alpha}_i)}{var(y_{ijt})} + \frac{cov(y_{ijt}, \hat{\gamma}_j)}{var(y_{ijt})} \end{aligned} \tag{1.9}$$

We expect a significant portion of model variation can be captured by the last term. We report our estimation results in Table 1.3.

[Table 1.3 about here.]

[14]See Cornelissen et al. (2008) for the detailed description on the computing algorithm of the Stata package "felsdvreg" which implements the AKM method. We use this package to estimate the AKM regressions.

Implementing the AKM method gives qualitatively similar and quantitatively stronger results than those in the Table 1.2. Starting from panel A where we consider the full sample, the manager fixed effects account for over 12% of the total variation of the model. While the F statistics seem moderate, taking the high level of degrees of freedom resulting from the almost 4000 managers into consideration makes it easily rejecting the null[15]. Fund fixed effects are still important, and they are almost just as important as manager fixed effects judging from the fraction of variation in our window dressing measure explained. Overall, panel A suggests that managers play an important role in deciding whether or not to window dress, in addition to fund level factors.

We confirm our confidence in suggesting the important role of managers in panel B and panel C. As explained before in Section 1.4.1, in panel B we use the subsample of restricted funds to address the concern that the observed manager fixed effects are just compressed by the fund restrictions to the extent funds allow them to show, which makes it hard to interpret whether the observed effects are fund or manager fixed effects. And in panel C, we use the subsample of worst performing managers in order to check whether funds intentionally hire candidate managers in order to window dress. There is no strong reason to believe that funds would hire those bad performers just to window dress. We find significant F statistics for manager fixed effects in both panel B and C. While the portion of sum of squares explained by managers now is smaller especially with the restricted funds subsample, it is nonetheless still meaningful.

In panel D we restrict the sample to single manager funds in order to have a clean interpretation of the results. Mutual funds can have large management and advisory teams. It is difficult to judge who of them play important roles, and who are only supporting staff. Restricting to single manager funds, however, do provide us with a clearer set up. We find strongly significant F statistic for the joint significance of the manager

[15]Checking the F table we can find the critical F statistics at this level of degrees of freedom are all slightly higher than 1.0000, and it does not vary much with 1%, 5% or 10% of significance levels.

fixed effects in this subsample. More importantly, these manager fixed effects explain more than 35% of the variation, much higher than those of the fund fixed effects, which account for only 7% of the explanatory power. Literature on team versus single mutual fund manager has long suggested there are at least two counter effects in determining fund policies. On the one hand, single managed fund has less coordination problem. On the other hand, team managers may have extra expertise in window dressing that single managers do not process (Adam and Guettler (2015)). Our finding that single managers have material impact on funds' decisions to window dress tend to suggest that single managers do have a lot of discretion, and this discretion could be the dominant effect when making investment decisions. We additionally test how manager fixed effects of a single manager in restricted funds differ from their unrestricted funds counterparties. While single managers in unrestricted funds do exhibit slightly higher explanatory power in explaining window dressing, we also observe significant F statistics with their restricted peers.

1.4.3 Out-of-Sample Forecast

If managers are important in shaping window dressing decisions, we might expect to detect a higher likelihood for a fund to start window dress when a pro window dressing manager joins. Thus we conduct an out of the period prediction and check whether our estimated manager fixed effects are meaningful in predicting fund managers' decision to window dress. We split the sample period into 2, before and after December 2006, and estimate manager fixed effects in the first period using the AKM method we used above. We define managers as pro window dressing if they are ranked in the top 30% in terms of coefficient[16] on manager fixed effects, and the bottom 30% as anti window dressing[17].

[16]The individual significance level of manager fixed effects does not matter since we are estimating so many manager dummies, it is the relative ranking of coefficients' economic magnitude that counts.

[17]The threshold 30% here is self-determined. In unreported tests we conduct a sensitivity analysis and choose 10% and 20% as thresholds. The estimated manager fixed effects have qualitatively similar

Using this definition, we check what happens when a pro window dressing manager joins a mutual fund in the second period. For each fund period, the net number of joining pro window dressing managers is equal to the number of pro window dressing manager joining minus the number of pro window dressing manager leaving plus the number of anti window dressing manager leaving minus the number of anti window dressing manager joining.

We test the prediction power in a multi-variant quasi DiD set up[18]. The baseline specification in column (1) of Table 1.4 is:

$$Y_{it} = \alpha_t + \beta Treated_i + \sigma Post \times Treated_{it} + \gamma X_{it} + \theta_j + \epsilon_{it} \tag{1.10}$$

Where Y is the window dressing measure for fund i in quarter t. X is a set of fund level controls. α denotes the quarter fixed effects. θ is the style fixed effects. Notice the dummy for post is omitted since time fixed effects are included.

[Table 1.4 about here.]

The regressions in columns 1 and 2 are on fund-period level. All standard errors are adjusted since we use estimated regressors. We find a significantly positive coefficient on the quasi-difference-in-differences estimator. Economically, a joining pro window dressing manager increases the probability of the fund to start window dress by almost 3 percent. This prediction power is even stronger if the manager is promoted. In column 2, we find an even higher probability for funds to start window dress when a joining pro window dressing manager moves from a smaller fund. One interpretation could be since managers are promoted, they may be more confident about their old strategies thus continue to window dress in the new fund. Here we estimate using linear probability model instead of the logistic model. Since we have some interaction terms, using linear models make the coefficient readily interpretable.

power in predicting funds' window dressing behavior as those estimated using the 30% threshold.

[18] We do not have a common event time since managers join funds in different time periods.

In columns 3 and 4 we directly put in our definition of pro and anti window dressing manager and estimate on manager(fund)-period level. Again we find pro window dressing managers, as defined by *first* period regressions, increase the probability of funds to window dress in the *second* period by 6.4%. We account for the time varying fund fixed effects by including fund-time fixed effects, the results are robust after including these terms.

1.4.4 Endogeneity

A potential concern with the manager story is that the match between managers and funds certainly is a choice variable and can be endogenously determined by funds. If the factors that lead funds to seek out window dressing manager candidates do affect the funds' decisions to window dress, then the manager effects we detected could be driven by those omitted factors. In this case, the manager effects would actually be fund effects.

Following the spirit of Adam, Burg, Scheinert and Streitz (2014) we employ a propensity score matching model and find the probability of a fund to have pro window dressing managers in the team. As a first step we collapse our data set to fund level and estimate this probability within the sample of first time period by regressing it on various fund characteristics. Agarwal, Gay and Ling (2014) find that fund performance, size, expenses and turnover ratio are significantly correlated with window dressing. We include these variables in this first stage regression. In addition, we hypothesize when funds are older, more established and more reputable they are less likely to window dress. As such we also include fund age and Morningstar rating[19] in the first stage[20]. Second, we predict in the second period sample the probability of a fund to have pro window dressing managers by utilizing the estimated first-period coefficient in the first stage. Assuming there is no structural change, the estimated coefficient will be applicable in the second period as well. We make out-of-sample predictions again to avoid the potential mechanical effect between having a pro window dressing manager and funds' decisions to window dress. Third, we match, in period 2 and according to the predicted probability of having window dressing managers, funds that having window dressing managers in reality and those funds that do not. Finally, we repeat the regression specification in columns 3 and 4 of Table 1.4 in this matched sample.

[Table 1.5 about here.]

We find pro window dressing managers increase funds' probability to window dress by over 6%, similar to the estimation results in columns (3) and (4) of Table 1.4. As a result, the out-of-sample test is robust after controlling for endogenous choice of fund managers. If the manager-fixed-effects-estimated definition of pro and anti window dressing can predict out-of-sample funds' decision to window dressing, we are more confident in attributing window dressing as a manager story in addition to a fund story.

If funds intentionally hire managers to window dress, they could add managers at a different rate comparing to those that do not window dress. We therefore test whether the managers in window dressing and non window dressing funds differ in terms of the duration of their positions hold. We find no evidence to support this counter argument.

We also conduct a placebo test in order to further address the endogeneity concern.

[19]Since data on Morningstar ratings are limited we estimate both specifications with and without the ratings and get similar results. The estimated probability we use in the matching results from the specification without the ratings.

[20]In untabulated results we find poor performing funds, larger and older funds are more likely to have a pro window dressing manager, while Morningstar ratings are not significant in explaining the probability.

If funds seek out managers to window dress, we would expect they may have already started window dressing even before the actual joining date of their candidates. Otherwise if the manager lead the changes, then it must happen after she/he joined the fund[21]. We assume managers join funds 3 years, 2 years, 1 year, 6 months, and 3 months before the actual joining date. The more distortion we introduce to the match between managers and funds, the less manager effects we should detect[22]. We report the results of the placebos in the following table:

[Table 1.6 about here.]

Following previous discussion we use the single manager sample in order to have a clean set up. From panel E where we assume managers join 3 months before their actual joining date to panel A where managers join 3 years before, there is a clear trend in terms of the estimation power of manager fixed effects. The explanatory power of manager fixed effects decrease monotonically with more distortion to the manager-fund match. Moreover, the correct specification in panel F has the highest estimation power of manager fixed effects among all. The results support our conjecture that manager leads the changes to funds' window dressing behavior.

1.4.5 Additional Concerns

Managers may drop out of our sample when they move outside the mutual fund industry. If such drop-out is correlated with whether they window dress, a potential survivorship bias emerge. We therefore check the duration of positions hold for window dressing and non window dressing managers. Window dressing managers on average hold the current

[21] See for example Cronqvist and Fahlenbrach (2009) for a similar implementation in a different context.

[22] Consider we assume the manager join 3 months before the actual joining date, if we check the entire career history of this manager, the portion that is correctly specified is after the actual joining date as well as three months before the actual joining date. Thus the more distortion we introduce, the less the portion of the career history that is correct.

position for 2.33 years, while others on average hold the current position for 2.29 years. The difference is not statistically significant.

One additional concern with our set up is that we have nearly 4000 managers, which is significantly more than those of the previous studies on manager fixed effects for example Bertrand and Schoar (2002), Graham, Li and Qiu (2012) and Ewens and Rhodes-Kropf (2015). Since we are testing against the null that all of managers are not significant in explaining window dressing, then if at least one of the manager is sensitive in making window dressing decisions, theocratically we should detect significant joint effect of significance for all managers. Thus we randomly split the managers into 10 groups with number of managers in each group comparable to those of previous literature, and check for the managers' role in each individual subgroup. We re-estimate using the AKM method and the results are reported below:

[Table 1.7 about here.]

In Table 1.7 we run 10 regressions, one for each group, using the AKM method. We find manager fixed effects are jointly significant in all of the 10 randomly split groups. The percentage of variation explained by the manager fixed effects vary from about 7% to 25%, with most fall into the 10% to 16% range. This is consistent with the results from the full sample test. With the number of managers comparable to previous studies, we confirm that manager fixed effects are jointly significant.

We provide a supplementary validity test of our estimated manager fixed effects by splitting the sample into 10 groups ranked by these effects. We then estimated the AKM manager fixed effects in each of these 10 groups. By construction, if our ranking (and implicitly our estimated manager fixed effects) is valid, we should expect manager effects to be most active in the groups with the highest and lowest full sample estimated manager fixed effects.

[Figure 1.2 about here.]

We confirm this hypothesis in Figure 1.2 where we find the subgroup 1, in which the managers have the most negative full sample manager fixed effects, and the subgroup 10, in which the managers are pro window dressing with the most positive full sample manager fixed effects, have both the higher F stats and explanatory power in terms of their within group manager fixed effects estimation. An U shape trend is observed from ranked group 1 to group 10. This adds to our confidence that our estimated manager fixed effects in Section 1.4.1 and Section 1.4.2 are meaningful in explaining managerial activeness in window dressing.

We further this analysis by completely randomize manager career history. Instead of drawing random samples, we drop the manager variable and assign 1000 randomized artificial managers to all of the observations. The simulation exercise is repeated for 10 times. If the concerns, that the manager fixed effects can be easily significant given we are testing against the null that none of the many managers are significant, is valid, then we would expect significance even in these randomized simulation results.

[Table 1.8 about here.]

None of the 10 randomized tests give significant manager fixed effects. The F statistics vary each time the model is simulated, but they remain insignificant. In the above table with one of the simulations[23], we find the manager fixed effect explains only a tiny percent of variation (0.5%), and the F statistic is only 0.93. Thus the manager fixed effects we detected with the real data are highly unlikely to be present by coincidence.

[23] Here only one simulation is shown since each simulation will give different results. The point is all of the simulations given consistently insignificant manager fixed effects.

1.5 Fund Interlocks and the Spreading of Window Dressing

By definition manager fixed effects can be detected only if the manager characteristics inherent do not vary over time. If managers' "fixed effects" vary over time, then our previous analyses will only find the lower bound of how manager would matter. We are still confident about our detected manager fixed effects because this bias is against us. In order to tackle this problem, in this section we take a different approach and test whether the level of interlocks, derived from number of common managers between fund periods, affects funds' decisions to window dress. The technique is straight forward. For every fund in our sample, we formulate fund period pairs. That is, we have an interlock measure for each and every fund period pair in the sample. Of course if in these two periods the two funds do not share any common manager, then their interlock level would be zero.

We re-estimate our baseline regression on fund-period-pair level, adding levels of interlocks and appropriate interaction terms, dropping manager fixed effects. The results are reported below:

[Table 1.9 about here.]

Various specifications give similar results. In column 2 for example, interlock is insignificant with an economically small positive coefficient. However, the interaction term of interlock and paired fund period's window dressing measure is highly significant and economically meaningful. If BHRG_pair equals to one, meaning that the paired was window dressing, then the higher the interlock level, the higher the possibility the new fund starts to window dress. If BHRG_pair equals to zero, then interlock level is not important in explaining window dressing. This intuitive result suggests that the practice of window dressing is indeed spreading across funds through interlocks, or the number of common managers, or, in the end, managers. We find the results are robust in both the switcher sample, in which the interlock between funds is established through manager turnover, and the multi-tasker sample, in which the interlock is established by managing multiple funds simultaneously. We do not find the spread of window dressing is more likely when the funds that manager worked for share geographical locations. Fund interlocks through common managers constitute a channel through which the practice of window dressing spread. They get exposed to the investment styles of different funds and carry the information when switching jobs.

One particular concern with this approach is spurious correlation. Since we use fund return to identify window dressing, this potentially introduces a correlation between the interlock and window dressing measures if managers select funds according to fund return patterns. However, there is no difference in return correlation between interlocked funds that window dress and those do not[24].

1.6 Conclusion

Employing comprehensive data set on manager career history of U.S. equity fund managers, we establish the connection between manager characteristics and the controversial and quasi-legal practice of window dressing. Going beyond the classical literature of window dressing which treats manager as homogenous and without any style, we find strong evidence that mutual fund managers significantly contribute to firms' decision to window dress. The result is robust after addressing endogenous matching concerns and powerful in making out of the sample predictions. Further we find fund interlocks affect window dressing decisions such that window dressing is spreading across funds through common managers.

Our analysis is meaningful especially for regulators. Mutual fund managers' compen-

[24]Return correlation between interlocked funds that window dress is 0.1889, and between interlocked funds that do not window dress is 0.1920. The difference in correlation is -0.0031 with a z score of -0.2269 and a p value of 0.8205.

sation is traditionally tied to their asset under management with a trend switching to performance based. If the quasi-legal practice of window dressing is a manager thing in addition to a fund thing, then the process of switch is very helpful since it reduces managers' incentive to window dress. Window dressing is certainly a negative practice at the cost of investors, and regulators may better incentivize managers not to window dress by enforcing performance based manager compensation.

Although we address the endogenous matching between managers and funds in several attempts. Ultimately we would need exogenous variations. Information on exogenous CEO departures, retirement or death are important in order to establish a clean test of causal relationship. In addition, testing the performance of pro and anti window dressing managers is also valuable, as the question of whether adding a pro window dressing manager is good or bad news for funds and for investors is crucial in maintaining a healthy and transparent industry in this regard.

Appendix

1.A Appendix A: Manager Attributes

As noticed in Bertrand and Schoar (2002), manager fixed effects themselves are not informative regarding what specific manager characteristics are important for their decision to window dress. It is therefore worthwhile to further address this issue by decomposing the black box of manager fixed effects. In particular, we hypothesize that managers' personal social network is an important factor in the spreading of window dressing especially in the current context of movers. We use the number of Linkedin connections as a proxy for managers' social and career network.

It is an open question whether managers with more Linkedin connections would be more or less likely to window dress. On the one hand, managers with more Linkedin connections are usually considered to be more reputable on average, and as such they should treasure their reputation and network to a larger extent than those with smaller number of Linkedin connections by refraining from window dressing. In addition, given the semi-private nature of window dressing, managers with more Linkedin connections are likely to be under the spotlight and therefore more cautious regarding such quasi-legal investment strategy. On the other hand, if the number of Linkedin connections can be a proxy for managers' personal characteristic to connect in the industry, it is possible that managers with more Linkedin connections are exposed to more information including the detailed "technique" of window dressing. Moreover, people tend to be more active over Linkedin when they have career needs. Managers with more Linkedin Connections are likely those moved more frequently between employers, thereby exposing to the investment style of different funds and carrying these information when switching jobs. If this is the case these managers with more Linkedin connections would have a higher possibility to window dress.

We extract the number of Linkedin connections, education background as well as bachelor's graduation year for all managers that once took the sole responsibility in managing a fund in our sample directly from their Linkedin pages[25], during which we require their Linkedin-listed career history to match those recorded in our data base[26]. We provide the summary statistics of the number of Linkedin connections in the table below.

[Table 1.10 about here.]

Notice when there are more than 500 connections, Linkedin shows the number of connections for such profiles as "500+". We therefore provide summary statistics for samples that including and excluding these cases. Over one quarter of the managers have a Linkedin profile with more than 500 connections. We additionally observe a high standard deviation in the number of connections among managers. In the analysis below we use two proxies, the number of Linkedin connections and a above average dummy, both coming from the data set that includes those "500+" profiles.

The Agarwal, Gay and Ling (2014) argument on window dressing as a risk bet with the presence of rational investors also imply that window dressing can be a signaling device. We hypotheses that personal education is a signaling device, and managers with a MBA or Ph.D. degree, or those graduate from prestigious universities are more likely to window dress. We are concerned if the number of Linkedin connections are proxies

[25]Notice we have only a snapshot of these data(cross sectional) and it is correct as of 30.06.2017. We expect them to be sticky variables.

[26]For cases we are not 100 percent certain, we extract the data with a question mark. Our results are robust to including those uncertain data points.

of manager entrenchment and therefore also include manager age or tenure to control for such effects. We also included the S&P 500 return of each manager's career start year as one of the manager characteristics. The logic behind is managers who start their career during market down time would be more cautious in making investment decisions as they spent greater amount of efforts in climbing to the current positions.

[Table 1.11 about here.]

We test these hypotheses in Table 1.11 along with a number of other manager characteristics. Managers with above median number of Linkedin connections have on average significant 2.93% higher backward holding return gaps even after controlling for manager entrenchment, suggesting managers window dress more when they are exposed to more information including the detailed "technique" of window dressing due to larger career network, or these managers work for more number of different funds, are educated and carry their style along the way. These effects dominate their reputation as well as cautiousness concerns when they have more Linkedin connections. Although we do find managers with Ph.D. are less likely to window dress, the power of estimation is limited by the number of managers that have a Ph.D. in the sample. We cannot find strong evidence to support the view that the stock market return of managers' career start year affects their window dressing behaviour. In untabulated results we also include whether the fund is incorporated in a liberal state or whether the manager is educated in a liberal state[27]. We have limited data and do not find these variables significantly explain fund window dressing behaviour.

These results shall be interpreted with caution and we are not making a causal statement here. The observed number of manager Linkedin connections could be the result of the endogenous matching between funds and managers. Funds may seek certain package of manager skills that happens to match that of a window dressing manager. While it is

[27] Following common practice we define a liberal state as one of the following: DC, VT, MA, DE, NY, HI, OR, ME, CA, NJ.

highly unlikely that the number of Linkedin connections is one of the factors when funds consider their candidates, the fact that certain managers have more Linkedin connections imply these managers may expost be selected more often than their peers. This imply these managers may have certain characteristics that matches funds' needs. And if the profile that funds are seeking coincide with those of window dressing managers, then the observed number of Linkedin connections can be endogenously determined.

While we cannot fully rule out this possibility, we provide a subsample test to argue for the generality of our results. We repeat the regression on manager attributes in a sample of bottom 20% performing managers. It is highly unlikely these managers possess the characteristics that the funds are actively seeking. We still find statistically significant coefficients on the number of Linkedin connections as well as the above median dummy.

1.B Appendix B: The Joining Effect-An Example

In this appendix we give an example that illustrates the joining effect of a pro window dressing manager.

[Figure 1.3 about here.]

We estimate manager fixed effects using the sample of the first period and detect the pro and anti window dressing managers. Manager A is among those pro window dressing managers. Manager A joins fund FSUSA004PD in January 2007, and stays in the fund until the end of 2012. We see the fund's tendency to window dressing suddenly improves after A joined the fund, suggesting the first period identification that A is a pro window dressing manager is meaningful.

1.C Appendix C: Are Manager Fixed Effects Fixed?

We show a figure on the persistence of window dressing measure. Of course we cannot draw any conclusion from this univariate analysis, but the average backward holding return gap is around zero before managers' first window dressing. After it shoot up at the first date managers start to window dress, which is by construction, it seems that managers consistently behave differently than before.

[Figure 1.4 about here.]

Figure 1.4 is consistent with the interpretation that window dressing is an inherent manager characteristic. Before exposing to window dressing, managers either do not have the knowledge, or do not possess the skill to window dress. They acquire necessary information and skill the first time they window dress. Although this is at odds with the Bertrand and Schoar (2002) assumption that manager style stays constant, which suggests we may have underestimated the importance of managers in window dressing.

Table 1.1: Descriptive Statistics on the Manager-fund Matches

The table reports the summary statistics on the matches between managers and funds. Movers are managers who have worked for more than one fund within the sample period, while stayers are those who have never moved. The sample comprises of 3976 managers, 1566 U.S. open end equity funds and 9346 unique manager-fund combinations between September 1998 and December 2014.

Panel A: Number of Funds Managers Ever Worked for			
Funds	Freq.	Percent	Cum.
1	1972	49.60	49.60
2	842	21.18	70.77
3	462	11.12	82.39
4	253	6.36	88.76
5	150	3.77	92.53
...	...	...	...
Panel B: Number of Movers, 1=Mover			
Mover	Freq.	Percent	Cum.
0	1972	49.60	49.60
1	2004	50.40	100.00
Panel C: Number of Movers per Fund			
Movers per Fund	Freq.	Percent	Cum.
0	86	5.49	5.49
1-5	99	6.32	11.81
6-10	68	4.34	16.16
11-20	150	9.58	25.73
21-30	112	7.15	32.86
31-50	267	17.05	49.94
51-100	446	28.48	78.42
>100	338	21.58	100.00

Table 1.2: Manager Fixed Effects on Window Dressing

The table lists the F test for joint significance of manager fixed effects. The dependent variables are BHRG, the backward holding return gap measure of window dressing, or BHRG 10%, a dummy variables that equals to one if the value of BHRG falls into the top 10% in each period. In panel A, the sample is the full (manager fund) year panel. Each row represents a regression. In each panel, the first row is the unrestricted model without manager fixed effects, and the second row is the restricted model with manager fixed effects. In each regression the control variables other than manager fixed effects are not displayed. The control variables include 3 months Carhart 4 factors alpha prior to the reporting date, fund trading activeness measure forward holding return gap, total net assets, expense ratio, turnover ratio, time fixed effects and fund fixed effects. In the cell of F statistics, the first number corresponds to F stat, with p values in the brackets. In panel B, the sample is divided to 2 parts according to the fund restriction measure of Almazan, Brown, Carlson and Chapman (2004), and the more restricted fund periods are included in the regression. In panel C, the sample is restricted to the funds for which managers with bottom 20% prior Carhart 4 factors alpha joined. In panel D, the sample is restricted to fund periods that are managed by a single manager.

Panel A: Full Sample			
DependentVar	F test on manager fixed effects	N	R^2
BHRG		138825	0.269
BHRG	7.0495415(<<0.01)	138825	0.276
BHRG 10%		138825	0.281
BHRG 10%	12.3352416(<<0.01)	138825	0.299
Panel B: Restricted Funds			
DependentVar	F test on manager fixed effects	N	R^2
BHRG		83682	0.117
BHRG	3.2718603(<<0.01)	83682	0.113
Panel C: Bottom 20% Performing Managers			
DependentVar	F test on manager fixed effects	N	R^2
BHRG		28063	0.263
BHRG	3.5426173(<<0.01)	28063	0.261
Panel D: Single Manager Funds			
DependentVar	F test on manager fixed effects	N	R^2
BHRG		11755	0.352
BHRG	12.2951363(<<0.01)	11755	0.394

Table 1.3: Manager Fixed Effects on Window Dressing using the AKM Method

This table reports the estimation results of the baseline regression using the AKM method. The dependent variables are BHRG, the backward holding return gap measure of window dressing, or BHRG 10%, a dummy variables that equals to one if the value of BHRG falls into the top 10% in each period. Each row represents a regression. Restricted model is the specification with manager fixed effects, while unrestricted model is the specification without manager fixed effects. $Cov \setminus Var$ denotes the fraction of the model sum of squares that can be attributed to manager or fund fixed effects. In each regression the control variables other than manager fixed effects are not displayed. The control variables include 3 months Carhart 4 factors alpha prior to the reporting date, fund trading activeness measure forward holding return gap, total net assets, expense ratio, turnover ratio, time fixed effects and fund fixed effects. In the cell of F statistics, the degrees of freedom are shown in the brackets. F statistics are given after the equal sign. Panel A utilize the full sample. In panel B, the sample is divided to 2 parts according to the fund restriction measure of Almazan, Brown, Carlson and Chapman (2004), and the more restricted fund periods are included in the regression. In panel C, the sample is restricted to the funds for which managers with bottom 20% prior Carhart 4 factors alpha joined. In panel D, the sample is restricted to fund periods that are managed by a single manager.

Panel A: Full Sample							
DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	No				F(1435,133714)=8.62		F(1566,133714)=8.62
BHRG	Yes	F(3975,133714)=3.5	0	.12904091	F(1435,133714)=7.94	.20700029	F(5410,133714)=9.76
BHRG10	Yes	F(3975,133714)=3.91	0	.18550102	F(1435,133714)=6.11	.17333261	F(5410,133714)=9.56
Panel B: Restricted Funds							
DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	Yes	F(2912,76160)=2.73	0	.06044505	F(907,76160)=6.35	.23538444	F(3819,76160)=8.23
Panel C: Bottom 20% Performing Managers							
DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	Yes	F(3590,23248)=2.23	0	.16288776	F(1254,23248)=3.01	.26729491	F(4844,23248)=3.65
Panel D: Single Manager Funds							
DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	Yes	F(676,10802)=6.37	0	.35164997	F(307,10802)=2.31	.07095909	F(983,10802)=7.88
Panel D.1: Single Manager Restricted Funds							
DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	Yes	F(482,7102)=5.66	0	.34319022	F(188,7102)=1.39	.02742369	F(670,7102)=6.38
Panel D.2: Single Manager Unrestricted Funds							
DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	Yes	F(241,1978)=6.71	0	.46169618	F(76,1978)=2.11	.11634308	F(317,1978)=7.75

Table 1.4: The Joining Effect of Window Dressers

The table presents the multivariate analysis on window dressing. The dependent variable is BHRG 10%, a dummy variables that equals to one if the value of BHRG falls into the top 10% in each period. Column 1 is a quasi-difference-in-differences estimation. Treated is a dummy variable that equals to one if a fund has increased amount of managers, and at the same time the net amount of joining window dressing managers identified by first period regressions is positive. Treated is equal to zero if a fund has increased amount of managers and the net amount of joining window dressing managers is not positive. Post is equal to one after the joining date. Promoted is equal to one if the joining managers move from a fund that has a TNA that is one standard deviation below the joining fund. All controls variables including the dummies of treated and promoted are not reported but included. The post dummy is not included. In each cell the reported are coefficients and t statistics. All standard errors are clustered at fund level. These regressions use linear probability model that estimated by least square. The stand errors are adjusted using bootstrap.

	(1) BHRG10	(2) BHRG10	(3) BHRG10	(4) BHRG10
Post*Treated	0.028***			
	(7.41)			
Post*Treated*Promoted		0.033***		
		(6.58)		
ProWD			0.064***	0.066**
			(5.78)	(2.00)
AntiWD			-0.009	-0.011
			(-1.46)	(-0.95)
Fund Controls	Yes	Yes	Yes	Yes
Observations	64214	64214	91140	91140
Time fe	Yes	Yes	Yes	No
Style fe	Yes	Yes	No	No
Fund fe	No	No	Yes	No
Time-Fund fe	No	No	No	Yes
Std Errors	Bootstrap	Bootstrap	Bootstrap	Bootstrap

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: The Joining Effect of Window Dressers with the Matched Sample

The table shows the second stage regressions of the propensity matched sample. The dependent variable is BHRG 10%, a dummy variables that equals to one if the value of BHRG falls into the top 10% in each period. The regressions are estimated in period 2, while the variable to construct the matching criteria, the probability for a fund to have pro window dressing manager(s), is estimated by a first stage regression (not tabulated) that uses the sample of period 1. ProWD and AntiWD is defined in the same manner as in Table 4 from the estimation results of period 1 sample manager fixed effects. All fund level control variables are included in this second stage. In each cell the reported are coefficients and t statistics. All standard errors are clustered at fund level. These regressions use linear probability model that estimated by least square. The stand errors are adjusted using bootstrap.

	(1) BHRG10	(2) BHRG10
ProWD	0.063***	0.069*
	(4.62)	(1.77)
AntiWD	-0.023*	-0.003
	(-1.66)	(-0.12)
Fund Controls	Yes	Yes
Observations	16396	16396
Time fe	Yes	No
Style fe	No	No
Fund fe	Yes	No
Time-Fund fe	No	Yes
Std Errors	Bootstrap	Bootstrap

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: Placebo Tests of Manager Fixed Effects on Window Dressing

The table lists the F test for joint significance of manager fixed effects, in which we assume managers join funds 3 years, 2 years, 1 year, 6 months, and 3 months before the actual joining date. The sample is the single manager fund manager-fund-year panel. The dependent variable is BHRG, the backward holding return gap measure of window dressing. Each row represents a regression. Each row represents a regression. In each regression the control variables other than manager and fund fixed effects are not displayed. The control variables include 3 months Carhart 4 factors alpha prior to the reporting date, fund trading activeness measure forward holding return gap, total net assets, expense ratio, turnover ratio, time fixed effects and fund fixed effects. In the cell of F statistics, the degrees of freedom are shown in the brackets. F statistics are given after the equal sign.

Panel A: Manager join 3 years before actual joining date

DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	Yes	F(454,8357)=6.88	0	.29058611	F(230,8357)=2.66	.09091353	F(684,8357)=7.22

Panel B: Manager join 2 years before actual joining date

DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	Yes	F(511,9552)=6.94	0	.3248104	F(255,9552)=2.61	.07318743	F(766,9552)=7.92

Panel C: Manager join 1 year before actual joining date

DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	Yes	F(532,10216)=6.94	0	.33208657	F(273,10216)=2.37	.06395732	F(805,10216)=7.98

Panel D: Manager join 6 months before actual joining date

DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	Yes	F(624,10601)=6	0	.33795209	F(304,10601)=2.13	.0728677	F(928,10601)=7.66

Panel E: Manager join 3 months before actual joining date

DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	Yes	F(609,10628)=6.43	0	.34162285	F(300,10628)=2.27	.0783856	F(909,10628)=8.14

Panel F: Actual joining date

DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	Yes	F(676,10802)=6.37	0	.35164997	F(307,10802)=2.31	.07095909	F(983,10802)=7.88

Table 1.7: Manager Fixed Effects in Random Split Samples

This table reports the estimation results of 10 randomly split sample tests using the AKM method. The dependent variable is BHRG, the backward holding return gap measure of window dressing. Each row represents a regression. $Cov \setminus Var$ denotes the fraction of the model sum of squares that can be attributed to manager fixed effects. In each regression the control variables other than manager fixed effects are not displayed. The control variables include 3 months Carhart 4 factors alpha prior to the reporting date, fund trading activeness measure forward holding return gap, total net assets, expense ratio, turnover ratio, time fixed effects and fund fixed effects. In the cell of F statistics, the degrees of freedom are shown in the brackets. F statistics are given after the equal sign.

Dependent Var: BHRG			
Group	F_Manager	$Prob > F$	$Cov \setminus Var$
1	F(388,11228)=3.82	0	.1489408
2	F(389,13733)=4.63	0	.1059992
3	F(393,12370)=5.19	0	.14282442
4	F(382,12670)=4.79	0	.15518244
5	F(387,13521)=4.46	0	.16975771
6	F(406,13677)=4.66	0	.07559424
7	F(414,14938)=4.13	0	.10148427
8	F(425,12909)=5.91	0	.25717685
9	F(387,12805)=4.92	0	.17005989
10	F(395,12744)=4.57	0	.15604634

Table 1.8: Randomized Managers and Simulation Results

This table reports the estimation results of the baseline regression using the AKM method, while the managers are simulated. The original manager variable is removed, and all of the observations are randomly assigned one of the 1000 artificial managers. The dependent variable is BHRG, the backward holding return gap measure of window dressing. Restricted model is the specification with manager fixed effects. $Cov \setminus Var$ denotes the fraction of the model sum of squares that can be attributed to manager or fund fixed effects. The control variables other than manager and fund fixed effects are not displayed. The control variables include 3 months Carhart 4 factors alpha prior to the reporting date, fund trading activeness measure forward holding return gap, total net assets, expense ratio, turnover ratio, time fixed effects and fund fixed effects. In the cell of F statistics, the degrees of freedom are shown in the brackets. F statistics are given after the equal sign.

DependentVar	Restricted Model	F_Manager	$Prob > F$	$Cov \setminus Var$	F_Fund	$Cov \setminus Var\_Fund$	F_Both
BHRG	Yes	F(999,136662)=.93	.9354	.00504442	F(1565,136662)=28.45	.24784946	F(2564,136662)=17.85

Table 1.9: Fund Interlock and Window Dressing

The table presents the multivariate analysis of fund interlocks on window dressing. The regressions are on fund period pair level. The dependent variables are BHRG, the backward holding return gap measure of window dressing, or BHRG 10%, a dummy variables that equals to one if the value of BHRG falls into the top 10% in each period. Interlock is defined as above in the text and normalized by dividing its standard deviation after subtracting the mean. Location is equal to one if the fund period pair share the same geographical location (U.S. states). In column (5) we restrict to the multitasking sample. In each cell the reported are coefficients (except for column (2)) and t statistics. All standard errors are clustered at fund level.

	(1) BHRG	(2) BHRG10	(3) BHRG	(4) BHRG	(5) BHRG
Interlock	-0.00321***	0.00212	-0.00335***	-0.00417***	-0.00124
	(-3.60)	(0.14)	(-3.69)	(-4.04)	(-1.50)
BHRG_pair	-0.00837		-0.0123**	-0.0129**	0.0165
	(-1.39)		(-1.99)	(-2.04)	(0.56)
Interlock × BHRG_pair	0.0213***		0.0268***	0.0241***	0.0459***
	(3.12)		(2.69)	(2.87)	(4.23)
BHRG10_pair		0.114***			
		(7.66)			
Interlock × BHRG10_pair		0.0413**			
		(2.25)			
FF4F		-0.0303*	-0.00424*	-0.00415*	-0.00266
		(-1.81)	(-1.65)	(-1.66)	(-0.78)
FHRG		-0.611*	-0.397***	-0.401***	-0.398***
		(-1.89)	(-8.01)	(-7.66)	(-7.69)
log(TNA)		0.0185*	0.00835***	0.00893***	0.0120***
		(1.81)	(3.50)	(3.65)	(4.37)
ExpenseRatio		17.35***	2.329*	2.251*	4.959***
		(4.13)	(1.76)	(1.79)	(3.18)
TurnoverRatio		0.0184**	0.0115**	0.0106**	0.0204***
		(2.55)	(2.58)	(2.38)	(5.10)
Location				0.00223	
				(1.46)	
Method	ols	clogit	ols	ols	ols
Marginal effects	No	YES	No	No	No
Sample	Switcher	Switcher	Switcher	Switcher	Multitasker
Observations	160488	135354	135354	123729	25178
R^2	0.571		0.630	0.632	0.620
Adjusted R^2	0.567		0.627	0.629	0.602
Time fe	Yes	Yes	Yes	Yes	Yes
Fund fe	Yes	Yes	Yes	Yes	Yes
Std Clustered	Fund	Fund	Fund	Fund	Fund

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.10: Summary Statistics on Single Manager Linkedin Connections

This table reports the summary statistics of the number of Linkedin connections for single managers. The statistics for the sample that includes and excludes managers with "500+" Linkedin connections are displayed separately. The data is extracted from managers' Linkedin profile, with career history matches those recorded in our data base. The data is provided as a snapshot and is correct as in 30.06.2017.

Including 500+		Excluding 500+	
Statistics	Number of Connections	Statistics	Number of Connections
N	868	N	620
Mean	274.932	Mean	184.9048
SD	189.6229	SD	148.1549
MIN	0	MIN	0
p25	100	p25	46.5
p50	271	p50	161.5
p75	500	p75	300
MAX	500	MAX	498

Table 1.11: Manager Attributes and Window Dressing

The table presents the multivariate analysis of manager characteristics on window dressing. The dependent variables are BHRG, the backward holding return gap measure of window dressing, BHRG 10%, a dummy variables that equals to one if the value of BHRG falls into the top 10% in each period, or BHRG 20%, a dummy variables that equals to one if the value of BHRG falls into the top 20% in each period. Number of connections is the number of Linkedin connections for each manager. Above median is a dummy variable that equals to one if the number of Linkedin connections of the manager is above median. S&P 500 is the yearly return on S&P 500 in the career start year of the manager. Tenure is calculated by the year difference between each year and the manager's career start year. In all 4 regression we include fund and time fixed effects, but not manager fixed effects. In each cell the reported are coefficients and t statistics. All standard errors are clustered at fund level.

	(1) BHRG10	(2) BHRG20	(3) BHRG	(4) BHRG
FF4F Alpha	-0.00172*	-0.00609	-0.000173***	-0.000173***
	(-1.66)	(-0.26)	(-2.72)	(-2.60)
FHRG	1.093*	1.355*	0.105	0.105
	(1.79)	(1.76)	(1.56)	(1.56)
ln(TNA)	0.0314	0.0546	-0.00209*	-0.00209*
	(0.84)	(0.90)	(-1.84)	(-1.85)
ExpenseRatio	-32.21	-21.72	-4.451**	-4.451**
	(-1.44)	(-0.68)	(-2.10)	(-2.10)
TurnoverRatio	0.0457	0.187**	0.0131**	0.0131**
	(0.81)	(2.62)	(2.37)	(2.37)
Number of Connections	0.000283**	0.000707***	0.0000426***	
	(2.35)	(3.69)	(3.33)	
Above Median				0.0293***
				(3.33)
MBA	-0.00417	-0.00894*	-0.0000352	0.0000963
	(-1.28)	(-1.95)	(-0.09)	(0.24)
PHD	-0.0770**	-0.138**	-0.00453***	-0.00408*
	(-2.24)	(-2.28)	(-2.63)	(-1.93)
S&P 500	-0.00502	-0.00957	0.00484*	0.00466*
	(-0.26)	(-0.37)	(1.76)	(1.77)
Tenure	-0.00330	0.0148***	0.00168***	0.00121***
	(-1.30)	(4.76)	(5.54)	(4.16)
Observations	3592	3592	3592	3592
R^2	0.322	0.409	0.294	0.294
Adjusted R^2	0.257	0.352	0.226	0.226
Time fe	Yes	Yes	Yes	Yes
Fund fe	Yes	Yes	Yes	Yes
Manager fe	No	No	No	No
Std Clustered	Fund	Fund	Fund	Fund

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

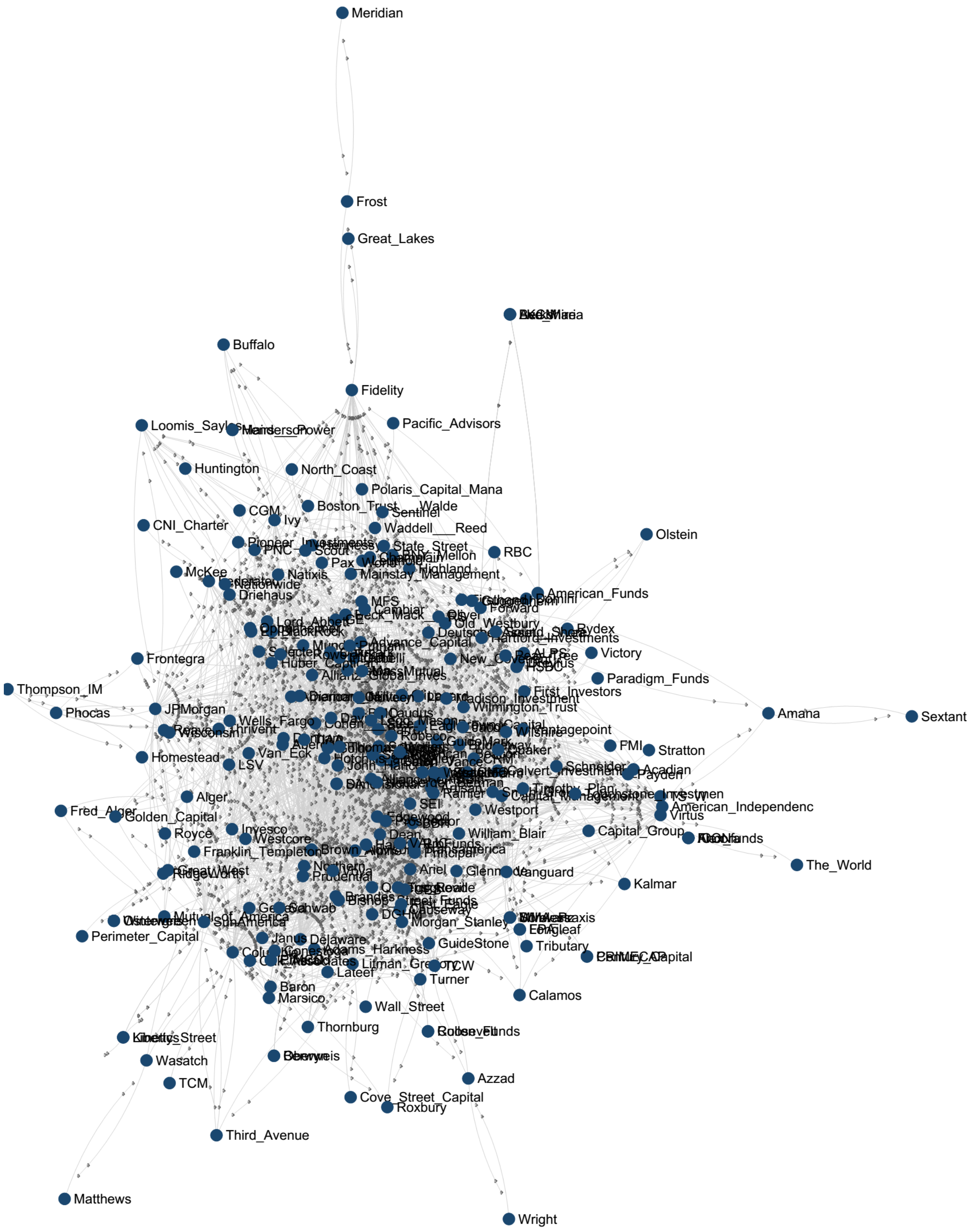


Figure 1.1: The Network of Mutual Funds Connected by Common Managers

The graph plots the mutual fund networks in terms of connected common managers. Each node represents a fund family (instead of mutual funds to make it visible) and each solid connecting line represents at least one manager that ever worked for both families.

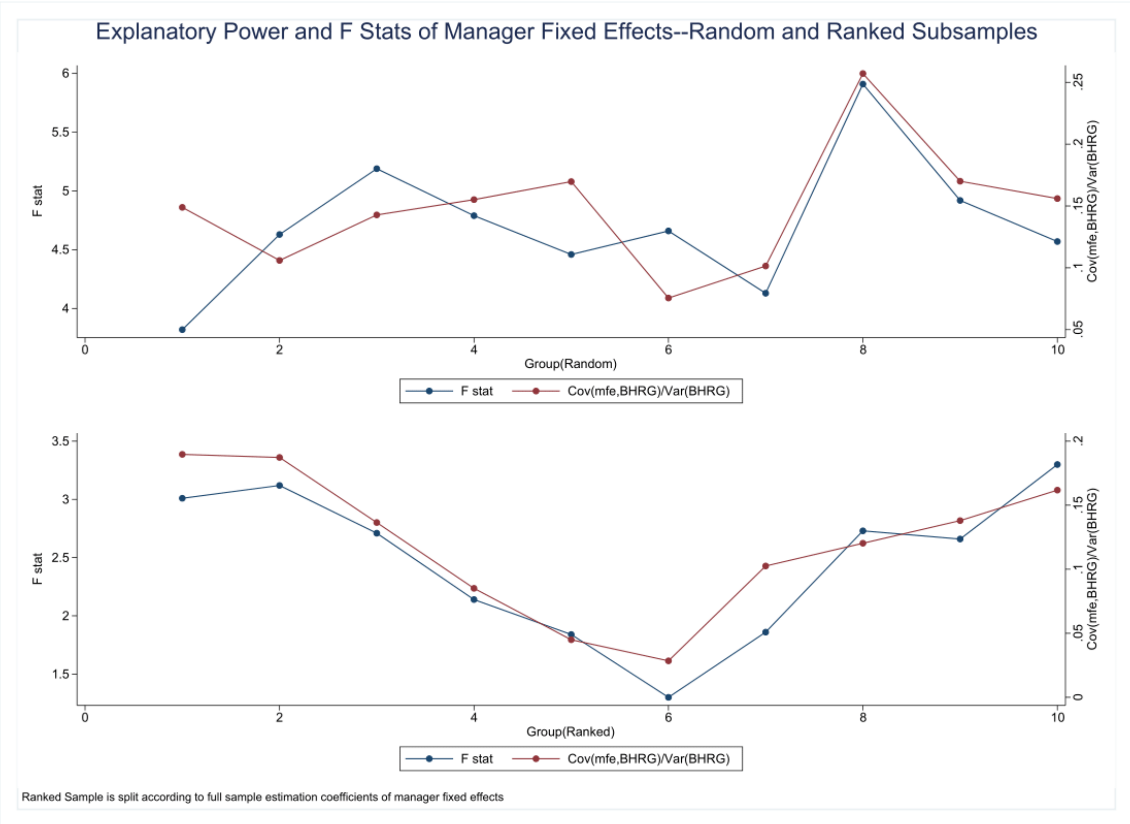


Figure 1.2: Explanatory Power and F Stats of Manager Fixed Effects–Random and Ranked Subsamples

The graph depicts the explanatory power and F stats resulting from the AKM manager fixed effects estimation for the random and ranked split samples respectively. Random and ranked split samples are as defined in Section 1.4.5. The ranking is determined by previous stage full sample estimation of manager fixed effects. The ranked group 1 has the lowest (negative) previous stage estimated manager fixed effects, while the ranked group 10 has the highest. F statistics and explanatory power are depicted on the left and the right axis respectively.

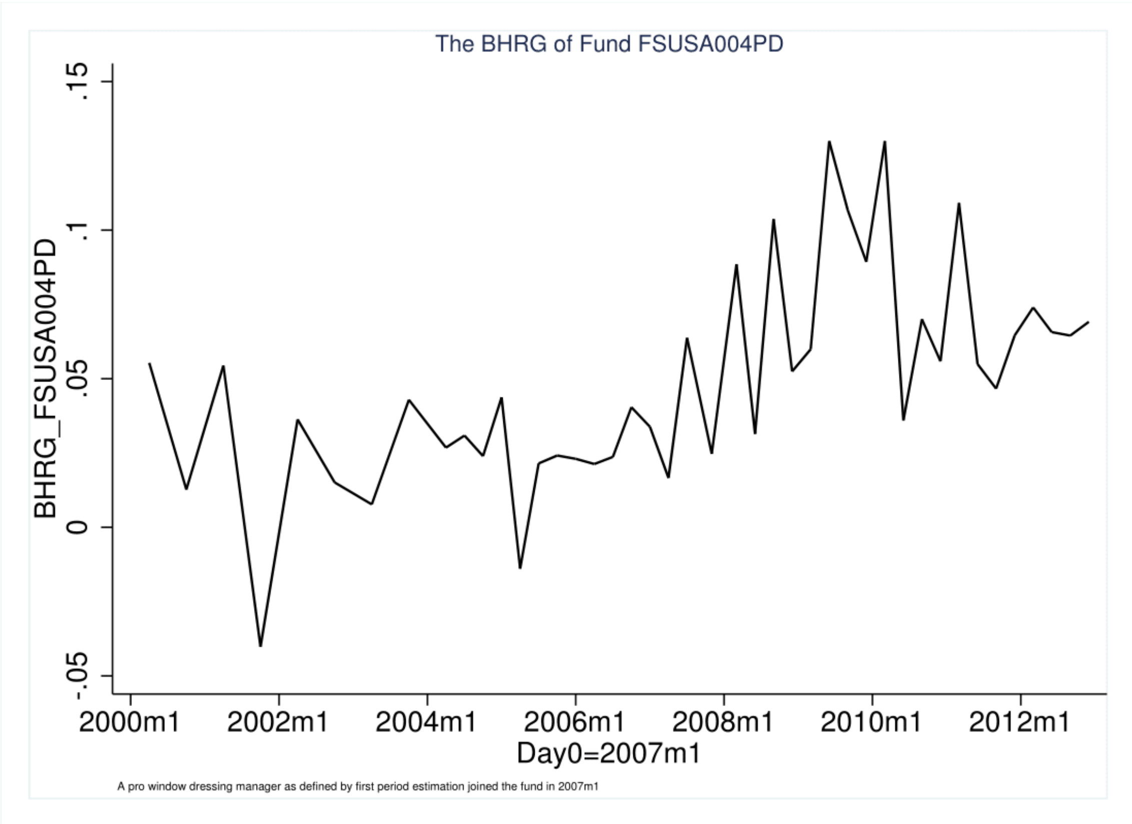


Figure 1.3: What Happens When a Pro Window Dressing Manager Joined?

The graph depicts the backward holding return gap after a pro window dressing manager joined with one particular example (Morningstar fund ID FSUSA004PD). The identified manager joined this fund in Jan 2007. The variable on the X axis is time, and the variable on the Y axis is the backward holding return gap of this fund.

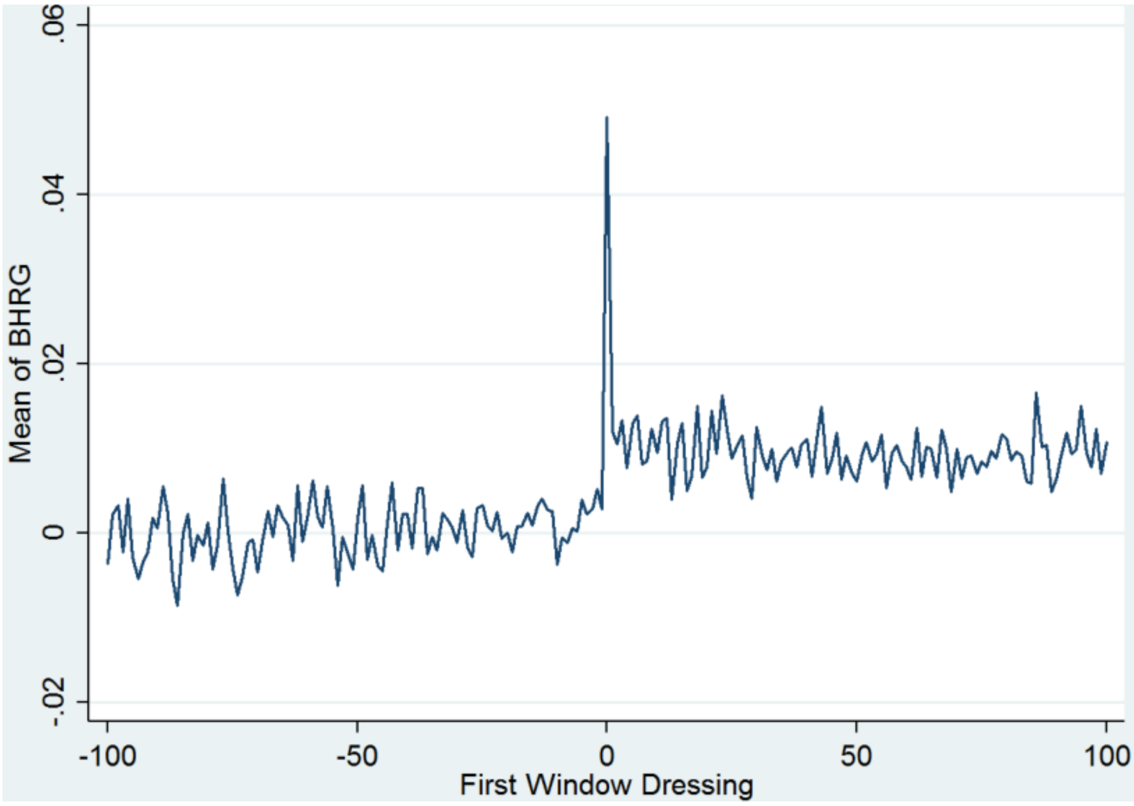


Figure 1.4: Manager Window Dressing Following the First Occurrence

The graph depicts average managers' window dressing after their first practices. For all managers in the sample we find their first window dressing date, as defined by BHRG 10% and shown as time equals to zero above, and tract them through time. The variable on the X axis is months before and after their first window dressing, and the variable on the Y axis is the average of backward holding return gap across managers.

Chapter 2

Mutual Fund CDS Strategies

Abstract

By matching U.S. fixed income mutual fund's Credit Default Swap (CDS) holdings collected from the SEC filings with their reported portfolio holdings from Morningstar, we examine the intended strategies when these CDS contracts are entered into, namely negative basis trading, hedging, bond synthesizing and speculating via naked long or short CDS positions. We find risk reducing incentives are dominated by speculative incentives, especially those to increase credit exposure via naked short CDS contracts. While other strategies are wide-spreading among CDS-using funds, negative basis trading motivated trades are, within the time frame of our estimation period, concentrated in few funds with highest total net assets. Experienced fund managers tend to take on more credit risk, while female managers are more likely to hedge comparing with their male peers. We confirm the existence of cross-fund-within-family trades facilitated by CDS. Fund family level strategic concerns overweight in-family fund tournament story in such trades.

Keywords: Mutual funds, Credit default swap, Portfolio management, Risk Management

JEL classification: G11, G23, G28

2.1 Introduction and Hypothesis Development

The U.S. mutual fund industry provides a justified laboratory to study the trading incentives of Credit Default Swaps (CDS). In order to pin down the motivation behind the CDS trades, it is essential to map the full portfolio set of these CDS-trading market participants, especially whether they hold the underlying of the CDS. This information is otherwise difficult to collect as CDS was traditionally traded over the counter with minimum transparency[1]. A few previous studies, notably Oehmke and Zawadowski (2016), acquire transaction level data of CDS from Depository Trust & Clearing Corporation (DTCC) and inspect CDS trading incentives by market-existing CDS positions and bond positions. Oehmke and Zawadowski (2016) find CDS is used for both hedging and speculation. Using bond outstanding volume as a proxy for hedging, and using analyst earnings forecast dispersion as a proxy for speculation, they find more CDS are traded on issuers that have more bond outstanding and for cases when analysts have disagreement regarding the reference entities' future performance. However, no direct evidence can be provided by these "macro" level analyses without looking from each market participants' perspective as they are eventually the entities making the investment decisions.

CDS involves the exchange (swap) of fixed-income securities' credit risk between CDS buyers and CDS sellers. Within the swap contract term, the buyer makes periodic payments to the seller and in return the seller compensates the buyer in credit events as defined in the contract. By the end of 2007, the outstanding CDS amount was 62 trillion USD, more than the total notional of all bonds outstanding. It had fallen to 29 trillion USD by the end of 2011 yet still plays a significant role in credit risk trading. One of the distinguishing features between insurance and CDS is that CDS may be held naked, i.e. without holding the underlying securities[2]. This feature amplifies

[1]This is gradually changing due to recent regulation changes, including central clearing and the introduction of swap execution facilities. However, CDS trades have not been incorporated into swap execution facilities yet.

[2]Except for naked long CDS positions written on EU sovereign debt starting from November 1, 2012, according to Regulation No.236/2012 of the European Parliament.

the concern over funds' ability to generate high implicit leverage at low costs through short CDS positions. AIG, Bear Stearns, Oppenheimer Champion Income Fund, among other funds, suffered from significant losses trading CDS during the global financial crisis. It is therefore worthwhile to ask what is the motivation that initiated the CDS trades.

The mutual fund industry is strictly regulated by the Investment Company Act 1940 (ICA) as well as its following amendments. All U.S. mutual funds have to report their portfolio holdings to the U.S. Securities and Exchange Commission (the SEC) in N-Q portfolio filings, semi-annual filings and annual filings[3], in which they need to detail all holdings, including derivative positions, as of each respective reporting period end. This provides us with an unique opportunity to match their CDS holdings with possible underlying bond holdings. For example, purchasing CDS on an existing bond portfolio could be of hedging motivations, while selling CDS and investing the corresponding notional into treasuries could synthesize a bond position. To the best of our knowledge, this is the first paper to facilitate such a match and investigate the CDS investment strategies on transaction level[4].

We start from the data set of Adam and Guettler (2015), detailed CDS contract information for the 100 largest U.S. corporate fixed income mutual funds from 07.2004 to 12.2010[5]. For each of the CDS holdings we identify the issuer of the underlying security that falls into one of the following categories: corporate, government, asset backed security (ABS), CDS index or bond index. We are able to identify 790 issuers in total. We then collapse the CDS data set from issue level to issuer level for each fund quarter because CDS are usually standardized contracts and even underlying and CDS

[3]The reporting frequency standard has been lifted in 2004. After 2004 funds have to file NCSR, NCSRS and N-Q reports with quarterly intervals.

[4]Jiang and Zhu (2015) and Aragon, Li and Qian (2017) also have detailed mutual fund holdings of CDS for periods 2007-2011 and 2004-2009 respectively. Yet there is no match between the underlying with the CDS and therefore one can only infer strategies by observing the buy/sell direction.

[5]For data extraction process and detailed sample description please refer to Adam and Guettler (2015) and Galkiewicz and Ma (2017). Out of these 100 funds, 66 have at least one CDS position outstanding during the sample period.

positions with different coupon rate and maturity can formulate combined strategies as well. We restrict to single name corporate CDS in order to have a clean analysis of CDS strategies[6]. For each fund quarter we match the issuer-level-collapsed CDS data with issuer-level-collapsed portfolio holdings data extracted from Morningstar Direct. For each *change* in the CDS positions we define it to be one of the following strategies: negative basis trading, hedging, speculation via naked long CDS, synthetic bonds, and speculation via short CDS (including speculation via naked short CDS, outright CDS).

We define the CDS strategies according to the changes in the CDS positions, the corresponding changes in the underlying positions (if there is any), the time sequence of these changes, the basis between the CDS market and the cash bond market when such changes occur, and the liquidity of the CDS and the underlying bond. Detailed features of these strategies are discussed in Section 2.2. CDS are usually standardized instruments with contracts following the guideline of the International Swaps and Derivatives Association (ISDA) master agreement. They have 5 years time to maturity when initiated and the most common practice to close existing CDS positions is to enter into offsetting positions. As a result, we separately consider cases when the entering long (short) CDS position offsets the previously held short (long) CDS position on the same issuer.

We formulate a number of testable hypotheses motivated by previous empirical and theoretical research on mutual fund investment strategies. There is mixed evidence on whether mutual funds use derivatives for hedging or speculation and yield chasing purposes. Koski and Pontiff (1999) and Cici and Palacios (2015) propose that equity mutual

[6]The majority of multi-name CDS are written on CDS indices and bond indices. Of course even with multi-name CDS we can also define CDS strategies in a way that is similar to our single-name CDS strategy definitions. For example, we could match CDS written on iBoxx USD Liquid HY to all bonds that are among the constituent of iBoxx USD Liquid HY index. However, this is not a practical solution as the matching will be contaminated by uncertainty. And the matching is even more questionable with CDS written on CDS indices, as the credit profile of CDS indices is correlated with those of the bond portfolio.

funds use derivatives primarily for risk reduction. This is consistent with the public perception that mutual funds as strictly regulated investment companies use derivatives mostly for hedging purposes. Complicated trading strategies like negative basis trading are traditionally considered as a hedge fund strategy. Two international studies Johnson and Wayne (2004) and Marin and Rangel (2006), however, document the risk increasing of mutual funds following derivatives transactions. Although there is no direct evidence on the CDS strategies of fixed-income mutual funds, it has been confirmed in a number of previous papers (Adam and Guettler (2015), Jiang and Zhu (2015), Galkiewicz and Ma (2017) and Aragon, Li and Qian (2017)) that bond mutual funds are on average net seller of CDS[7]. Our first hypothesis is therefore related to funds' strategies in trading CDS.

Hypothesis 1: Fixed-income mutual funds trade single name CDS for various reasons including to trade negative basis, to hedge, to speculate via naked long CDS, to synthesize bonds, and to speculate via short CDS, among which the short speculative strategy is the dominant strategy.

In contrast to the public perception, we find hedging motivated transactions constitute only 6.22% of all mutual funds' single name CDS trades. Instead, speculative strategies, especially selling naked CDS, are the dominant strategies during the sample period. In the time periods leading to the financial crisis, speculative strategies, especially via short CDS, gained enormous popularity. These positions declined rapidly post crisis. On the long side, CDS purchases are more likely to be negative basis trading or speculating via naked long CDS than hedging. Negative basis trading was most widely used immediately following the crisis when there is convergence of the CDS basis.

We formulate testable hypotheses regarding the determinants of the defined strategies.

[7] Galkiewicz and Ma (2017) notice the possibility of funds using CDS to bypass the 5% diversification rule, that funds cannot invest more than 5% of their TNA to securities of one single issuer.

First, CDS is a complicated credit derivative and CDS trading would require expertise to implement. Additionally, a typical CDS contract has a size of 5 million U.S. dollars and therefore would be more conveniently used by larger funds (Adam and Guettler (2015)), we therefore hypothesize that larger funds would engage in more CDS strategies. Investment grade funds would potentially use less CDS since their assets are relatively safe with less rationale in hedging. And their profit from gaining credit risk exposure via short CDS is also limited by the quality of CDS they sell. However, Adam and Guettler (2015) find investment grade funds hold more junk CDS (in percentage of total CDS held) than their junk bonds (in percentage of total bonds held), while high yield funds hold less junk CDS comparing with their junk bond holdings. They also document investment grade funds are more likely to trade CDS, and are insignificant in explaining net short CDS positions. The authors attribute the results to investment grade funds may have more incentive to shift risk since their performances are clustered, therefore a minor change in performance is meaningful. It is therefore an open question how do investment grade funds use CDS comparing with high yield funds and we speculate that investment grade funds trade more CDS for risk reduction purpose since they wish to minimize price impact, and trade less CDS for speculative purposes due to credit risk control[8].

Second, we formulate hypotheses on a number of manager characteristics. Young and less established managers are more risk-averse than their established peers due to higher termination risk (Chevalier and Ellison (1999a)). The compensation of longer tenured managers is less sensitive to their performance. Additionally, investors seem to punish more established managers less when their funds underperform because of trust and reputation (Wu, Wermers and Zechner (2016)). It is therefore reasonable to hypothesize older managers and those with more experience would trade more speculative CDS po-

[8]This is not necessarily inconsistent with Adam and Guettler (2015). For example, an investment grade fund invest 10% of its TNA into junk bonds, and 90% into investment grade bonds. Now the fund purchases CDS to protect its 10% junk bond position. In this case, the fund would have 100% of CDS invested in junk CDS.

sitions, e.g. selling CDS to load up on credit risk. Chevalier and Ellison (1999b) argue that quality of education (and hence professional network) matters for manager decision making. Given the complexity in CDS trading, we propose that better educated managers use more CDS strategies that are unorthodox (i.e. other than hedging). There is a stream of literature on whether there is prejudice towards women in management and how female managers perform in comparison with male managers. Some view men as more overconfident than women and female managers tend to make risk-averse investment decisions (Odean (1998), Barber and Odean (2001) and Niederle and Vesterlund (2007)). We therefore hypothesize that female manages tend to hedge more and trade less speculative CDS strategies. However, also notice Atkinson, Baird and Frye (2003) find female mutual fund managers do not exhibit significantly different managerial style comparing with men.

Hypothesis 2a: A number of fund characteristics are correlated with the propensity to trade CDS with various strategies. Larger funds are more likely to trade CDS. Investment grade funds are less likely to speculate but more likely to hedge with CDS.

Hypothesis 2b: Older and more experienced managers trade more speculative CDS e-specially naked short CDS (Outright CDS). Managers graduated from prestigious universities or with advanced degrees are less likely to hedge when they use CDS. Female managers in contrast take on more CDS for hedging purposes.

We investigate the above hypotheses regarding the determinants of CDS strategies in a probit panel set up on fund quarter level. While we find funds with larger TNA are more likely to trade negative basis, through data inspection we find negative basis trades are concentrated in only two funds while all other CDS strategies are relatively wide-spread. In terms of managers' effects on CDS strategies, we find older managers, more experienced managers and those with top educational background are more likely to buy naked, sell naked or to synthesize a cash bond. Older and more experienced managers hedge less of their underlying comparing with their younger peers. Female managers have 7.9%, 17.4%, and 9.6% higher probabilities to trade negative basis, to hedge, and to purchase naked long CDS respectively.

CDS strategies could be a proxy of broader fund family level strategies. In the Appendix A of this article we examine cross-fund-within-family trading strategies facilitated by CDS, whether they exist, and how do we interpret them. There is a sizable literature on fund competition and corporation within families[9]. One the one hand, fund families would be better off if their fund portfolio have diverse investment styles because of the well-documented convex flow-performance relationship (Sirri and Tufano (1998) and Chevalier and Ellison (1997)). It provides the rationale to achieve family level diversification and product differentiation. Family level strategic trading, cross-fund trading and cross-fund subsidization emerge as a result. On the other hand, starting with Brown, Harlow and Starks (1996) who record mid-year losing funds gamble for end of the year returns[10], tournaments within families are also discussed. We are concerned if the naked positions that we defined are truly naked, i.e. if the underlying can be matched in other funds in the family to formulate cross-fund strategies or to reveal fund competition. If the tournament hypothesis dominates the cross-fund CDS trades, we would expect funds with risk-averse managers to take opposite directions in trading CDS when their performances are close (Basak and Makarov (2014)). However, if the fund level strategic decision story is more relevant, we should observe diverging performance for funds trade in opposite direction with one of them purchasing naked long CDS and its peer holding the underlying.

[9]See for example Gaspar, Massa and Matos (2006), Evans (2010), Nanda, Wang and Zheng (2004), Massa (2003), Bhattacharya, Lee and Pool (2013), Brown and Wu (2016), Eisele, Nefedova and Parise (2016), and Cici, Jaspersen and Kempf (2017) on family level strategies, cross fund trades and subsidization; Brown, Harlow and Starks (1996), Kempf and Ruenzi (2007) and Basak and Makarov (2014) on fund tournaments.

[10]It can also be attributed to the convex flow-performance relationship.

Hypothesis 3: Cross-fund trading and subsidization story better explains cross-fund matched CDS trades.

We are able to match the underlying with similar notional in other member funds in 122 cases (out of 895) for naked long CDS positions, and 89 cases (out of 912) for naked short positions. Funds taking naked short CDS positions are classified as in the same trading direction with their matched peers in the family that hold the underlying bond. Similarly, funds entering into naked long CDS positions are classified as in the opposite trading direction with their matched peers. We find funds with opposite directional trades facilitated by CDS exhibit a statistically significant 0.38% quarterly 5-factors alpha difference on average.

Our paper extends the existing knowledge over several streams of literature. First of all, our paper is related to the effort in explaining strategies and motivation behind CDS trades. By matching CDS with their underlying held concurrently by market participants, we add to this literature by defining CDS strategies on transaction level without having to refer to the aggregate market volume of CDS and bonds, or to make informed projections by observing the buy or sell signs of CDS only. Oehmke and Zawadowski (2016) find the number of bond outstanding predicts the CDS outstanding, which likely suggests that CDS is used for hedging. At the same time more CDS are observed on reference entities that analysts have disagreement regarding their future performance. The authors attribute this to speculative activities. Fontana (2011) and Bai and Collin-Dufresne (2011) document the negative CDS basis during the global financial crisis and attribute the basis to funding risk, funding cost, collateral quality, counterparty risk, and liquidity factors. Oehmke and Zawadowski (2015) model CDS as a non-redundant security due to their lower trading costs. The model predicts negative CDS basis. These researches on negative basis trading motivates us to check the strategy from the market participants' perspective.

Second, the article adds to the literature on the use of CDS by financial institutions as well as mutual funds' derivative use. Mutual fund industry is considered as a minor player in CDS trading, yet the severe losses to the industry during the financial crisis due to CDS should remind us of the importance in understanding the details of these positions. There are a number of papers that cover mutual funds' derivative use. Koski and Pontiff (1999) and Cici and Palacios (2015) provide diverging evidences from Johnson and Wayne (2004) and Marin and Rangel (2006) on whether there are differences in performance and risk between equity mutual funds that use and do not use derivatives, predominantly options. The first two document risk reduction in using options, while the latter two international studies state the opposite. There is also a stream of literature that looks at the use of CDS and other financial institutions. Mahieu and Xu (2007) and Minton, Stulz and Williamson (2005) study the use of CDS by banks. However, due to adverse selection and moral hazard problems the CDS market for usual bank exposures is relatively illiquid. Hirtle (2009) finds bank credit supply is positively related to greater CDS use only for large term loans, which may suggest the results are accruing to large firms with established reputation. In a paper that studies the risk and performance implications of hedge funds' use of stock options, Aragon and Martin (2012) suggest hedge funds possess significant timing and picking skills. The underlying stock's return and volatility can be predicted by the option holdings of hedge funds.

The papers that are most closely related to this article in terms of the subject of investigation are Adam and Guettler (2015), Jiang and Zhu (2015), Galkiewicz and Ma (2017) and Aragon, Li and Qian (2017). However, our paper has a very different research focus. Adam and Guettler (2015) focus on the performance and risk of team managed CDS using funds and compare them with those of single managed CDS using funds. The argument is on the costs and benefits with teams, i.e. more expertise, experience and skills vis-á-vis coordination problems. The financial crisis is employed as a natural experiment as long decision times are extremely costly during adverse and rapid changing markets. Jiang and Zhu (2015) provide evidences on the liquidity provision role of the CDS market. Galkiewicz and Ma (2017) study the manager characteristics that are correlated with funds' CDS use, yet CDS strategies are proxied by long and short CDS positions only. Aragon, Li and Qian (2017) exam a number of hypotheses related to general CDS use in the mutual fund industry with a focus on counterparty risk. We add to this literature by pinning down the CDS strategies of mutual funds and relate the detailed strategies to fund and manager characteristics[11]

Third, we shed additional light on cross-fund trading and subsidization with a specific type of transaction. Each single name CDS has a specific underlying security that may be held by other funds in the family. A natural and direct link therefore can be established on transaction level. Nanda, Wang and Zheng (2004) show fund families benefit from diverse investment strategies across funds by attracting more fund inflows. This is consistent with the convex flow-performance relationship of Sirri and Tufano (1998) and Chevalier and Ellison (1997). A number of papers, including Massa (2003), Gaspar, Massa and Matos (2006), Bhattacharya, Lee and Pool (2013), Brown and Wu (2016), Eisele, Nefedova and Parise (2016), and Cici, Jaspersen and Kempf (2017) document the existence of cross-fund trading, learning and subsidization from various aspects[12]. However, none of them provide direct evidence on transaction level. We fill the gap in this regard.

The rest of the paper is organized as follows. Section 2 discusses the data sources and sample construction. In Section 3 we formally define the CDS strategies based on the match between CDS with its underlying security and provide summary statistics. The question what strategies do mutual funds employ when trading CDS is answered in

[11]See for example Chevalier and Ellison (1999a), Wu, Wermers and Zechner (2016), Chevalier and Ellison (1999b), Odean (1998), Barber and Odean (2001), Niederle and Vesterlund (2007) and Atkinson, Baird and Frye (2003) for behaviour stories in the mutual fund industry.

[12]Basak and Makarov (2014) formulate a theoretical framework to study these issues.

this section. Determinants studies on CDS strategies are presented in Section 4. Section 5 concludes. Appendix A deepens our analysis to the cross-fund level.

2.2 Data and Sample Construction

The primary data set is quarterly CDS holdings of the top 100 U.S. fixed-income mutual funds for the sample period 07.2004 to 12.2010, which is identical to Adam and Guettler (2015)[13]. This information has been gathered from NQ, NCSR, NCSRS filings recorded in SEC Edgar database and the commercial Edgar Pro database. Given the CDS data is available quarterly after 2004, we keep all other data matched to the CDS data in quarterly intervals whenever possible. The definition of the top 100 fixed-income bond funds is based on their TNA as of the end of quarter two of 2004, and for funds that fall into the following Lipper category: corporate debt funds A-rated, corporate debt funds BBB-rated, short investment grade, short-intermediate investment grade, intermediate investment grade, multi-sector income, and high current yield (Adam and Guettler (2015)). Among mutual funds CDS are primarily used by fixed-income funds by their design. And the top 100 bond funds already capture the majority of the market capitalization of all U.S. bond mutual funds during the sample period (Adam and Guettler (2015)). These 100 funds were followed towards the end of the sample period to avoid survivorship bias. Unique identifiers are assigned and kept as the primary match key. For each CDS position, its notional, market value, buy/sell sign, counterparty and underlying information are extracted from the filings. Please refer to Adam and Guettler (2015) for detailed discussions on the CDS data extraction of this sample.

We need fund holding data in order to inspect the match between CDS and its underlying. In order to facilitate the cross-fund match, we gather fund holdings not only

[13]We are grateful for the data provided by Adam and Guettler (2015).

for the top 100 sample funds, but also all funds that belong to the families of these 100 funds. This data set has been acquired from Morningstar[14]. Fund level characteristics such as fund name, family, manager(s), TNA, daily and monthly returns, turnover ratio, expense ratio, fund class, and shares held by institutional investors are obtained from CRSP survivorship bias free mutual fund database. The CRSP data is collapsed from share class level to fund level following common practice. Variables are TNA-weighted when appropriate. Fund TNA is the aggregate across all share classes. For managers of the sample funds we follow Galkiewicz and Ma (2017) to collect manager level characteristics from Morningstar, with Bloomberg, fund reports, and fund official websites as supplements. In particular, we gather manager's age, experience (in years) working for the top 100 funds, gender and educational background. Manager characteristics are team-adjusted as in Galkiewicz and Ma (2017)[15].

We extract CDS basis of the CDS holdings (BLP_CDS_BASIS_MID), market spread of CDS, as well as underlying bond z spread and asset swap spread from Bloomberg[16]. We pick the issue with 5 years to maturity whenever possible (or closest) to collapse

[14]Notice Morningstar also has CDS and other derivative holdings recorded for the funds, yet the quality of the data is questionable and the underlying of the CDS is usually not recognizable. Researchers usually resort to Edgar for CDS holdings. In order to check the data quality of Morningstar for usual bonds holdings, we calculate the sum of the market values (and sum of notional values) of all portfolio holdings for each fund quarter as reported by Morningstar, and compare it with the TNA as reported by CRSP. We find that in 84% of the fund quarters the difference between total Morningstar holdings and CRSP TNA is less than 10% (of the respective CRSP TNA value), and in 91% of the cases the difference is less than 20% of the CRSP TNA. The Morningstar (non-derivatives) holding data has been widely used. For example Elton, Gruber, Blake, Krasny and Ozelge (2010) and Cici and Gibson (2012) suggest the data is of high quality. Elton, Gruber and Blake (2011) recommend Morningstar holdings over Thomson holdings. There are potential biases with the Morningstar data since it is voluntarily reported. The authors compare the fund characteristics of reporting Morningstar funds with those of CRSP fund universe, and they find no significant difference. We have a problem, however, for the top 100 bond funds sample in 11 out of the 2557 fund quarters we are missing Morningstar holdings and this could be due to voluntary reporting. All of the 11 cases are in 2004 or 2005. We therefore conduct robustness checks on our CDS strategy definitions and determinants studies with data after 2005 and find no observable difference for the coefficients and significance levels in the determinants studies. In 2 out of the 11 cases the CDS strategy definitions are affected yet it is minimum to change the landscape of the defined CDS strategies.

[15]We take average for manager age and experience with team setting. For female dummy, top-20 university dummy, and master degree and Ph.D. degree dummies, the team has a dummy value equals to one if at least one of the team members is attached with a value one in the respective dummy.

[16]We extract the bid, ask and mid values of these data items. Liquidity of bond or CDS is calculated by ask minus bid price.

the data from issue to issuer level following common practice[17]. We measure counterparty risk by the default probabilities (1-month, 3-months, 12-months, 24-months, and 60-months)[18]. This information is obtained from National University of Singapore Risk Management Institute (RMI). For the factors model calculating risk adjusted fund performance we obtain Barclays indices including Barclays aggregate, Barclays Corporate High Yield, Barclays Intermediate Gov, and Barclays GNMA from Datastream. We additionally collect industry classifications based on SIC codes from Fama-French repository. A sample summary statistics table is provided below[19].

[Table 2.1 about here.]

The funds in the sample have a median TNA of more than 2 billion U.S. dollars. Managers of these funds are on average 44 years old with more than 2 years of experience in the top 100 funds. Roughly half of the management teams have at least one manager that graduated from a prestigious top 20 university, or graduated with a master's degree. Ph.D. degree holders and female managers are rare in the sample funds. The 1 year default probabilities of CDS counterparties are on average 2 percent[20]. The CDS basis is on average negative during the sample window, which covers the crisis period that we observe dramatically negative basis.

Our primary data set starts with 45100 individual CDS holding entries for the top 100 funds during 07.2004 to 12.2010. In order to define CDS strategies on transaction level, we match the CDS positions with their underlying bonds for each fund quarter. The match is essentially being conducted on the name basis. As a first step, we identify the issuer names for each of the 45100 CDS positions' underlying. 45100 CDS in our sample have been written on 790 distinct issuers (e.g. General Motors). Next, we

[17]Bond spreads can be linearly interpolated by two option free bonds with more and less than 5 years to maturity.

[18]The median holding periods of the CDS positions are 4 quarters, we therefore employ the 1 year default probabilities in the analysis.

[19]Panel A of the table replicates table 2 of Galkiewicz and Ma (2017).

[20]Mutual funds' CDS counterparty are predominantly major investment banks.

collapse the CDS data from issue level to issuer level. The 45100 issue level observations for all our fund quarters are reduced to 15750 issuer level observations, with 3343 multi-name issuer level observations, and 12407 single-name issuer level observations[21]. This suggests on average there are roughly three CDS entries per underlying issuer per fund quarter. Notional values, net notional..etc. are collapsed accordingly. During the collapse long and short CDS positions are collapsed *separately*, i.e. if there are both long CDS and short CDS written on the same issuer for a fund quarter, they do not offset each other[22]. Third, for each of the 790 issuers we search through Bloomberg and Datastream for all of their possible ISINs by checking all of their bonds outstanding. We abstract CUSIPs from the ISINs, and further the first six digits of CUSIPs from CUSIPs. The first six digits of CUSIPs, which we call them CUSIP6, are issuer-specific and identify issuers. Notice issuers are likely to have multiple CUSIP6s. Now we assign the CUSIP6s to all of our 15750 issuer level observations on 790 issuers. Fourth, Morningstar portfolio holdings are coming with ISINs. In a similar way we generate CUSIP6s for each of the holding entries for all our sample fund quarters. We collapse the holding data from issue level to issuer level. Finally, for each fund quarter the issuer level CDS data is merged with and matched to its holding data, with CUSIP6 as the merging key[23].

Now we arrive at the data set with CDS holdings and portfolio holdings for all sample periods on issuer level. CDS and portfolio holdings are matched if they are on the same issuer. This is the data set we base our CDS strategies definitions on. From now on we will restrict the attention to single name CDS positions. Since funds report their holdings instead of transactions, as an initial step we calculate quarterly issuer level CDS position changes for each fund. Although we do not observe trades between each report-

[21] Multi-name CDS is on average larger in notional size per position. The total notional of multi-name versus single-name CDS is roughly 45:55. See Galkiewicz and Ma (2017).

[22] CDS contracts can be closed by entering into offsetting positions. We, however, do not observe a large number of offsetting positions (433 out of 15750) and the treatment of the positions do not significantly affect our results.

[23] The process is being supplemented by direct name matches, and double checked by manual inspection. In a manual check of data in 10 random fund quarters, we do not find any errors in the matching of CDS with their underlying bonds.

ing period end, the CDS position changes indicate possible trades during the period. We have 1724 cases in which funds increase issuer level CDS notional in long CDS positions comparing with previous quarters; 2100 cases of short issuer level CDS increases; 319 cases of long CDS decreases; and 766 cases of short CDS decreases. For the 1724 long CDS entering and 2100 short CDS entering, we define the CDS strategies in Section 2.3.

2.3 CDS Strategies and Summary Statistics

In this section we formally define CDS strategies based on observable data[24]. One particular concern is that the observed fund/manager actions may not be fully representative of the true incentives and mindsets. We therefore use the word "strategy" loosely. It refers to the observed actions, with a good chance reflecting the thought process.

2.3.1 Negative Basis Trading

Basis is the spread difference on the same asset between cash and derivatives markets. CDS basis is therefore the difference in spread between CDS and their underlying asset, usually bonds, and is calculated as CDS spread minus bond spread. CDS spread can be represented by either the reported CDS premium or market CDS spread, with market spread being more commonly applied. We use (interpolated) z spread as a proxy for bond spread and derive CDS basis. This solution is also provided by Bloomberg (CDS_Basis_BLP_Mid). Z spread is the fixed spread adjustment to the risk free curve which gives the market value of the bond. That is, the value of z given by the following[25]:

$$P = \frac{c}{f}\sum_{n=1}^{N}\frac{1}{(1+(r_f+z)/f)^n} + \frac{1}{(1+(r_f+z)/f)^N}$$

[24] We greatly benefit from the discussion of the strategies with Tim Adam, Dominika Galkiewicz and Andre Guettler. We thank them for the contribution.

[25] Bai and Collin-Dufresne (2011) propose to use CDS implied bond spread. See appendix A of their paper.

In a frictionless market the CDS basis should be zero since bond spread (e.g. z spread) measures the credit risk one exposed to when entering into the cash bond position. And CDS insures the same credit risk. However, there could be liquidity risks, counterparty risks, mispricing...etc[26] that effectively drive the basis away from zero. Given the existence of negative basis, negative basis trades explore the difference in spreads by purchasing the CDS and the underlying bond simultaneously, and finance the cost at risk free rate or repo rate. The negative basis will eventually narrow near common maturity[27]. Without considering liquidity and counterparty risk factors as well as funding costs, investors can lock in a profit. The distinguishing features of negative basis trades are entering with negative basis, simultaneous purchasing, and similar or identical amounts purchased in the cash and the derivatives market, we therefore define an increase in long CDS positions as negative basis trading if it satisfies[28]:

- There is an increase in the issuer level long single-name CDS position comparing with the previous quarter (either from zero or from a nonzero number). There is an increase in the corresponding matched issuer level underlying bond position comparing with the previous quarter.
- Both increases happen at the exact same quarter[29].
- The notional amounts of both increases have a difference of less than or equal to

[26]See for example Garleanu and Pedersen (2011), Oehmke and Zawadowski (2016), Oehmke and Zawadowski (2015), Fontana (2011) and Bai and Collin-Dufresne (2011).

[27]This is due to the replicability of the CDS cash flow.

[28]We have imposed a number of thresholds in the definitions. Some are justified by existing empirical research. For example, according to Fontana (2011) and Bai and Collin-Dufresne (2011), the entering basis has to be less than -10 basis points for the strategy to be profitable because repo and reverse repo rates can be different from risk free rate, we therefore choose -10 basis points as the cutoff for highest possible basis when entering negative basis trades. Some cutoffs, however, are assigned. For example, we need the entering notional amount of CDS and the underlying to be identical or similar to lock in the profit of trading negative basis. We impose the 10% as the maximum acceptable difference. This value therefore has to be subject to sensitivity analysis, in which we find slight but insignificant variation in the number of defined strategies and determinants study with the change of the threshold.

[29]We do find indicative supporting evidence that funds entering into long CDS position and its underlying at the same time target at basis trading. For all of the issuer level CDS observations for all fund quarters, CDS basis is negative for 63% of the cases. For those observations with funds entering into long CDS and its underlying at the same time though, CDS basis is negative for 91% of the cases.

10% of the increase in CDS notional[30].

- The CDS basis of the entering CDS position is less than or equal to -10 basis points[31].

The CDS basis was turning dramatically negative during the financial crisis. In Figure 2.1 we depict the time series of the distribution of quarterly average CDS basis for *all* CDS contracts of the sample funds during the sample period.

[Figure 2.1 about here.]

The median CDS basis is close to zero and marginally positive before 2007. At the height of the financial crisis, we observe a median basis of less than -300 basis points, and the variance of the basis also escalated. The basis remains negative post crisis, but the median CDS has a basis that is only slightly negative and it is unclear whether a median CDS can still facilitate a profitable negative basis trade.

Applying the above definition of negative basis trading we find 432 out of the 1724 long CDS investments can be classified as trading on negative basis[32]. This result, however, should be acknowledged with caution since the cases of negative basis trading are highly concentrated in two funds (which accounts for over 70% of the negative basis trading cases.). Our determinants that explain negative basis trading (in Section 2.4) are therefore heavily influenced by the characteristics of the two funds. Towards the end of Section 2.3 the time series plot of the number of negative basis trading cases is shown

[30]If the difference is larger than 10%, we label the position as not classified to have clean definitions.

[31]Since the CDS data is on quarterly intervals and we do not have information on when during the quarter the trade takes place, we use the quarterly average of the weekly CDS basis to decide whether the entering basis meets our requirements. Alternative choices would be to use quarterly minimum basis (that yields more trades fit the definition), quarterly maximum basis (that yields less trades fit the definition) or quarter end basis. We report the number of negative basis trades for these alternative choice of basis as well, but keep the number resulting from quarterly average basis in the follow-up analysis.

[32]Using quarterly minimum basis as the qualifying condition we have 446 cases of negative basis trading. Using quarterly maximum basis we have 409 cases. In 399 out of the 432 negative basis trading cases the amount of the long CDS notional entered is identical to the amount of bond notional purchased. We would have 440 cases of negative basis trades if we relax the requirements to 20% in difference of notional values.

together with the plot of the other strategies.

Positive basis trades are in general not possible with bond mutual funds since they are not permitted to take short positions on fixed-income securities. However, if the CDS basis temporarily became even wider, it may be plausible to entering into CDS and the underlying bond simultaneously as well. We document 43 cases in which funds entering into long single name CDS position and the underlying position with similar notional amounts at the same quarter when the CDS basis is actually positive.

2.3.2 Hedging

Hedging with CDS involves purchasing CDS on existing bond holdings. The long CDS position serves to insure the credit risk of underlying. The distinguishing features are taking a long single-name CDS position, and hedging existing portfolio. In a sense negative basis trades are also hedged since negative basis traders are effectively protected from the credit risk of the underlying, although basis trading is for yield chasing and arbitrage purposes and the incentives behind is very different from hedging. Hedging and negative basis trading motive can exist at the same time as well. In the current context, we exclude negative basis trading from the definition of hedging and classify an increase in long CDS positions as hedging if it satisfies:

- There is an increase in the issuer level long single-name CDS position comparing with the previous quarter (either from zero or from a nonzero number).
- There exists the corresponding matched underlying bond position in the current quarter. There exists the corresponding matched underlying bond position in the previous quarter.
- The transaction is not being classified as negative basis trading.

If the increase of long single-name CDS positions makes the CDS notional on the issuer to pass through the notional of the respective bond, then the fund is over-hedging. Over-hedging can be due to duration matching considerations. Among the 1724 long single-name CDS increases, 238 are defined as hedging, out of which 81 are over-hedged by at least 10% of the underlying bond notional. This is in contrast to the public perception that mutual funds use CDS primarily for hedging while other CDS strategies are more common among hedge funds.

2.3.3 Speculating via Naked Long CDS

Entering into a naked long CDS position without holding or purchasing the underlying is essentially a bet on the deterioration of the underlying company's credit quality. The strategy is of speculative nature since funds only profit from it if the specified credit event was triggered. The funds are also exposed to additional counterparty risk by utilizing the strategy. If the naked long CDS positions are highly volatile over time, it adds to our confidence in defining a speculative strategy. A special case, however, would be funds entering into naked long CDS positions written on financial institutions in order to hedge against the counterparty risk of their various derivatives positions, including interest rate swaps, credit default swaps...etc. The credit exposure is not properly reflected by observing the bond portfolio holdings only, and naked long CDS positions on derivative dealers can constitutive hedging strategy as well. We therefore exclude naked long CDS on financial institution underlying from cases of speculating via naked long CDS strategy[33]. Due to the difficulties in quantifying the relative counterparty risk exposed to[34] and hedged in these cases, they are also excluded from the definition of hedging strategy. We classify an increase in long CDS positions as speculating via naked long CDS if it satisfies:

- There is an increase in the issuer level long single-name CDS position comparing

[33]The definition of finance industry is based on the Fama-French 12-industry classification with SIC ranging from 6000 to 6999.

[34]This is not limited to the counterparty risk due to CDS trading.

with the previous quarter (either from zero or from a nonzero number).

- There is no corresponding underlying bond position in the current quarter[35].

- The issuer of the bond underlying the naked long CDS is not a financial institution.

Among the 1724 long single-name CDS increases, 781 are defined as speculating via naked long CDS. Depending on the interpretation, the 81 cases of over-hedged CDS can also be considered as speculating.

2.3.4 Bond Synthesizing

Synthetic bonds involves selling CDS and at the same time investing the notional amount into treasuries. The strategy replicates the cash flow of the underlying bonds (securities). Bond synthesizing is implemented for various reasons. Funds may diversify their portfolio by entering into synthetic positions due to cost or liquidity reasons. Synthetic bonds are cheaper than cash bonds when the CDS basis is positive (with low bond spread and high bond market price), and cash bonds may be liquidity constrained for funds to purchase. Mutual funds may also create synthetic positions to bypass the 5% diversification rule[36]. Therefore, depending on market conditions, synthetic positions may have more attractive features over cash bonds[37]. We classify an increase in short CDS positions as bond

[35]We acknowledge that funds may purchase CDS in order to hedge against the credit risk of a portfolio bond issuer that have high correlation with the CDS underlying issuer in terms of credit worthiness. For example, taking a naked long CDS position on Ford is likely to constitute at least a partial hedge against the bond holding of General Motors. It is therefore a judgement call whether to match on exact issuer, or to match on some even more loose definitions like industries. Due to the controversy in implementing the SIC code based industry definitions, we match on exact issuers. Caution in interpretation should be noticed. Our strategy speculating via naked long CDS refers to naked CDS positions without underlying holding, it can be possible a correlated asset is present in the bond portfolio. But since the match is based on issuers and not issues, correlation within issuers is not a problem here.

[36]We do not observe such practice in our sample funds.

[37]Our paper primarily focuses on single-name CDS. An interesting topic for future research is the synthetic positions on multi-name CDS. Multi-name CDS are written on bond indices, CDS indices, asset backed securities (ABS), and asset backed security indices (ABX). Synthesizing positions provide handy opportunity to gain exposure to a basket of credit risks, which is otherwise difficult and costly to achieve without CDS. Before the global financial crisis, ABS and ABX products were growing in popularity and liquidity constrained. The CDS on ABS and ABX therefore were well accepted since there is no limit on how many derivatives can be issued on the asset backed securities.

synthesizing if it satisfies[38]:

- There is an increase in the issuer level short single-name CDS position comparing with the previous quarter (either from zero or from a nonzero number).
- The CDS basis of the entering short CDS position is greater than 0 basis point[39].
- The bid ask spread of CDS is smaller than the bid ask spread of the bond.

Among the 2100 short single-name CDS increases, 597 are defined as bond synthesizing.

2.3.5 Speculating via Short CDS and Outright CDS

Similar to holding the bond portfolio directly, short CDS positions positively expose the funds to the credit risk of the underlying. Therefore in a sense by synthesizing bonds, funds are also "speculating" that the underlying is not going to default. In this paper we refer the strategy speculating via short CDS to the speculative short CDS strategy that does not involve bond synthesizing incentives. Selling CDS without simultaneous investment in treasuries is cash equivalent to purchasing the underlying bond, and borrowing the notional amount from a bank. The strategy effectively generates implicit leverage and can be potentially significantly riskier than a cash bond position[40]. If the underlying of the short CDS can be found in the bond portfolio, then the short CDS position adds to existing bond position in terms of credit risk. If CDS position is sold naked, which is called outright CDS, the strategy can serve to diversify the existing portfolio, but also at the same time impose additional implicit leverage. CDS, especially either speculative naked long CDS or speculative short CDS, can be motivated by market timing. Purchasing CDS at low credit risk premium and selling similar CDS during periods with high credit risk premium may realize an arbitrage gain. However,

[38] We do not incorporate the changes in treasuries into the definition. Cash and cash equivalent holdings can change for various reasons other than bond synthesizing and is not a clean variable to use.

[39] Similar to the definition of negative basis trading, the choice of CDS basis could be either quarterly average, quarterly minimum, quarterly maximum or quarter end. We use the quarterly average of the weekly CDS basis to define the synthetic bonds strategy.

[40] Mutual funds are required to keep the explicit leverage ratio to be below 33.33%, yet short CDS positions may help funds to bypass this rule.

this strategy is also of speculative nature and is not explicitly listed separately. All short single-name CDS increases that are not synthetic bonds are classified as speculating via short CDS:

- There is an increase in the issuer level short single-name CDS position comparing with the previous quarter (either from zero or from a nonzero number).
- The CDS basis of the entering short CDS position is negative or zero.
- The bid ask spread of CDS is greater than or equal to the bid ask spread of the bond.
- If there is no corresponding underlying bond position in the current quarter, the strategy is further defined as speculating via naked short CDS, or outright CDS.

Among the 2100 short single-name CDS increases 1503 are defined as speculating via short CDS, out of which 912 are outright CDS.

2.3.6 Summary Statistics on CDS Strategies

In this subsection we provide some summary statistics on the defined CDS strategies. As a first step we briefly summarize the definitions in Table 2.2.

[Table 2.2 about here.]

Notice for all of the 2100 short single-name CDS increases, a strategy is assigned. However, the defined long strategy cases do not exhaust the full set of the 1724 long single-name CDS increases, with cases like simultaneously entering into long CDS and underlying with positive basis, and naked long CDS on counterparties been excluded from the list. Therefore, the number and fraction of issuer level cases in each strategy are given in Table 2.3 and Figure 2.2:

[Table 2.3 about here.]

[Figure 2.2 about here.]

We find the short CDS speculative strategy is by far the predominant CDS strategy employed by the top 100 U.S. fixed-income funds for the sample period of Q3.2004 to Q4.2010 and it accounts for two-fifth of all CDS deployments. Combined with the strategy speculating via naked long CDS, around 60% of the CDS use are of speculative nature. Negative basis trading and bond synthesizing are popular as well, although it should be noticed that negative basis trading cases are clustered in few funds. Most surprisingly, hedging incentive is not an important driven factor when mutual funds considering CDS investment. Instead, yield chasing, diversification and credit exposure seeking attract funds to invest in CDS. One natural concern is the crisis period falls into the sample period and there was significant volatility of CDS basis during the period. Credit environment as well as the public perception may also change following the crisis. It is therefore interesting to check the time series development of the CDS strategy deployments.

[Figure 2.3 about here.]

The time trend of the total number of case counts in all five strategies is in alignment with the big picture of Adam and Guettler (2015). CDS are most widely used during the periods leading up to the financial crisis, and dramatically declined in popularity after the crisis. Funds build up significant speculative positions just before the crisis, and these positions were largely resolved after 2009Q1. The number of negative basis trades escalated in 2008Q4. Funds may have sensed the significant basis in 2008Q4 would soon start to converge. Hedging is relatively popular during the crisis, yet the magnitude of the number of hedging cases is still not comparable to speculative and basis trading strategies.

2.4 The Determinants of the CDS Strategies

In this section we further describe the data set by conducting a determinants study and check which funds and which managers are more likely to engage in each of the CDS strategies. The analysis is on fund quarter level[41], in which we collapse the defined strategy to fund quarter level such that as long as there exists at least one issuer level defined CDS strategy for the fund quarter, the fund is said to have engaged in that quarter. The estimation focuses on fund and manager characteristics and it serves to test Hypothesis 2a and Hypothesis 2b. With a logit panel model, we estimate the following:

$$Y_{it} = \alpha_t + \beta X_{it} + \sigma Z_{it} + \epsilon_{it} \tag{2.1}$$

Where Y is the CDS strategy for fund i in quarter t. X is a set of fund characteristics of interest. Following Adam and Guettler (2015) we include TNA, fund age, institutional, investment grade, expense ratio, and turnover ratio in the regression. Z is a set of manager characteristics we need to test[42]. β and σ are vectors of coefficients. α denotes the quarter fixed effects. We report the estimation results in Table 2.4.

[Table 2.4 about here.]

In contrast to our hypothesis that larger funds are more likely to trade CDS, we find funds with higher TNA are only more likely to engage in long CDS strategies, among which only two funds dominate the estimation results of negative basis trading[43]. This is probably due to the sample itself contains only top 100 funds in terms of TNA. Investment grade funds are more likely to hedge and to speculate via naked long CDS, yet

[41] The analysis is based on all 100 funds and all 26 quarters, with CDS non-users also included in the panel.

[42] Manager characteristics are collapsed to fund level at well. Manager age and top 100 fund experience are averaged across management teams. For education and gender dummy variables, as long as one of the team member has the value of the dummies equals to one, the fund (and the team) is assigned a value of one in the fund level education and gender dummies.

[43] In fact all coefficient estimates on negative basis trading are basically reflecting the determinants of limited number of funds.

are less likely to speculate via short CDS. We believe this can be due to the Adam and Guettler (2015) interpretation on the excessive sensitivity of investment grade funds to performance. Consistent with previous literature, turnover ratio and expense ratio are in general higher for funds trading CDS.

Older managers and managers with more top 100 fund experience are possibly entrenched, less risk-averse and less likely to have job security concerns (Chevalier and Ellison (1999a)and Wu, Wermers and Zechner (2016)). The empirical observation is completely in line with this argument. Manager age is positively correlated with the probability of short CDS strategies, and is negatively correlated with hedging. Managers graduated from a top 20 university or with a master's degree have 4.3% and 3.6% less probabilities to hedge comparing with their counter groups respectively. Top 20 University and master variables are also positively correlated with short CDS strategies with economically large and statistically significant coefficients[44]. Adam and Guettler (2015) find female managers are less likely to trade CDS, especially short CDS. We find female managers have a 17.4% higher chance to hedge comparing with their male peers.

In order to address the interdependencies in the CDS strategies, we conduct an alternative set of tests that employ the multinomial logit model. Since CDS strategies are not mutually exclusive, a fund can enter into multiple strategies in one quarter. We define the dominant strategy of each fund quarter as the strategy with the highest notional of CDS. This categorical variable is then used as the dependent variable in the multinomial logit analysis. We acquire qualitatively similar results as in the previous discussions in this section. The details of the analysis is reported in Appendix B.

[44]There are few managers with Ph.D. degree, therefore the coefficients on Ph.D. are driven by few candidates.

2.5 Conclusion

The focus of the paper is to classify and document CDS strategies of fixed-income funds and to take a trial on analyzing cross-fund-within-family CDS strategies. There is an extensive list of literature that studies CDS strategies with aggregate market data, and a few papers on mutual funds' use of CDS. Yet the CDS underlying has not been matched with the portfolio of the holding entity. Only by matching the two one can define CDS strategies on transaction level.

We employ the top 100 U.S. fixed-income mutual funds as the laboratory to facilitate the matching, with CDS data covering the period from 2004Q3 to 2010Q4. The financial crisis period is included so that the time series variation of each CDS strategy deployments during and outside of the crisis can be inspected. We find, in contrast to the public perception that mutual funds as regulated and transparent investment companies predominantly trade CDS for hedging purposes, that speculative strategies, including speculating via naked long CDS and speculating via short CDS, accounts for around 60% of total CDS use for the sample fund period, with speculating via short CDS as the most frequently used strategy. In an effort to determine the factors that are correlated with the decision to conduct each of the CDS strategy, we document older and more experienced managers, managers with advanced degree or graduated from a prestigious university are more likely to speculate via short CDS and less likely to hedge, while female managers hedge more than their male peers.

We match the naked CDS positions to portfolio holdings of other funds in the family in order to disentangle between two conjectures. The first one being the family level trading, diversification, subsidization and corporation story which predicts diverging performance for funds that form opposite direction cross-fund trades in the family. The other one is the within-family fund tournament hypothesis that predicts funds take opposite direction cross-fund trades when their competition is fierce and performance is close. We find when funds formulate opposite direction cross fund trades via CDS, there is a significant difference in terms of quarterly 5-factors alpha of 0.38% between the identified cross fund traders. We conclude family level strategies story dominates in this regard.

Appendix

2.A Appendix A: Cross-Fund Strategies within Fund Families

In this appendix we further explore the implications of the CDS strategies and test whether these could be proxies of broader fund as well as fund family level strategies. According to ICA 1940 article 17a-7, cross trades and cross subsidization of money management firms are permitted as long as there are fair valuation of the assets and equal treatment of both trading parties. It has long been noticed these cross trades are widespread phenomenon in the industry. For example, financial times writes on this issue:

In house trades (cross trades)...It has happened many times in the past, ...In 2008 it was one way to ensure that prime money market funds would be protected, says Jean-Baptiste de Franssu, a former chief executive of Invesco Europe. I am aware that it happens, ... I suspect it is quite widespread, says another senior European industry figure who wishes to remain anonymous.[45]

There is a sizable literature that studies within fund family competition and corporation. One the one hand, some argues that fund families as incorporated companies have their strategic values in manipulating fund level strategies. Fund families could explore the

[45] See Financial Times article No surprise at backroom dealing charge [`https://www.ft.com/content/875e7e80-42e5-11e2-aa8f-00144feabdc0`, visited on 22.08.2016]

convexity of the flow-performance relationship as there are asymmetric responses of flow for good and bad performing funds[46]. Thus having a good and a bad performing fund would attract more flow than having two similar average fund. In this case it makes sense to take opposite directions in fund level transactions and for those families that do they could attract more inflows after implementing cross strategies proxied by CDS cross strategies. There are also values in family level diversification, product differentiation, information sharing within families. Eisele, Nefedova, Parise, Peijnenburg et al. (2017) find cross trades exhibit significant mispricing which leads to manipulated superior performance of star funds in the family. If wealth transfer through cross trades is possible, it provides the rational to implement cross fund strategies involving CDS. Gaspar, Massa and Matos (2006) and Evans (2010) document that families strategically transfer performance across member funds to favor those with high fees at the expense of low value funds. Goncalves-Pinto and Sotes-Paladino (2016) model cross trades as a way to smooth liquidity shocks in the family[47]. On the other hand, fund tournaments and within family competition are also well documented in the literature, starting from Brown, Harlow and Starks (1996) that look at how mid-year losers gamble for end of the year performance. Kempf and Ruenzi (2007) provide evidence on tournaments within fund families. Basak and Makarov (2014) model the dynamic portfolio choice of funds competing in the family. Two risk averse fund managers would choose to gamble in opposite directions when their performances are close.

It is therefore an open question whether funds that take opposite directional trades within families would exhibit similar or diverging performances. If the fund family level strategies story dominates, these funds would have differentiable performances either due to product differentiation and diversification, star fund creation or convexity exploration concerns. We are, however, not able to further distinguish among the three arguments

[46]For flow-performance relationship see Sirri and Tufano (1998) and Chevalier and Ellison (1997).

[47]See also Nanda, Wang and Zheng (2004), Massa (2003), Bhattacharya, Lee and Pool (2013), Brown and Wu (2016), Eisele, Nefedova and Parise (2016), and Cici, Jaspersen and Kempf (2017)

in this paper. If the within family tournament story dominates, these funds should have similar performances as funds that are tied are more likely to engage into competition.

For each entering naked positions that we have defined (both long and short), we match them to the portfolio holdings[48] for *all* other funds in the fund family in the same time period. Since mutual funds are restricted to take short positions on bonds, we define trades that are on the same direction (SD) as the CDS using fund is selling naked while the underlying is found in other fund in the family. Similarly, trades are on the opposite direction (OD) if the CDS using fund is purchasing naked while the underlying is being held by its peers. We are able to match the underlying with similar notional in other member funds in 122 cases (out of 895) for naked long CDS positions, and 89 cases (out of 912) for naked short positions. For each quarter and each family, we define two funds to be on the same side (SD) or opposite side (OD) according to the netted number of SD cases or OD cases respectively.

We estimate a panel regression with the following specification. The panel variable is fund pairs (paired within fund families).

$$abs[\Delta\alpha_{(ij)t}] = OD_{(ij)t} + SD_{(ij)t} + abs[\Delta\beta_{(ij)t}] + \delta_t + \gamma_{(ij)} + \epsilon_{(ij)t} \tag{2.2}$$

where $abs[\Delta\alpha_{(ij)t}]$ is the absolute value of the difference between fund performances of fund pairs. Following Adam and Guettler (2015) bond fund performances are proxied by raw return, 1-factor alpha, 3-factors alpha, 4-factors alpha and 5-factors alpha[49].

[48]Again since the CDS positions are collapsed to issuer level, portfolio holding are also collapsed to issuer level.

[49]The factors includes are: 1-factor alpha: return on Barclays aggregate index minus the risk free rate; 3-factors alpha: Fama-French three factors returns; 4-factors alpha: Barclays aggregate index return in excess of risk free rate, an equity market excess return as in Fama-French, Barclays Corporate High Yield Index return minus Barclays Intermediate Gov index return that accounts for default risk, as well as a mortgage market factor Barclays GNMA index return minus Barclays Intermediate Gov index return; 5-factors alpha: Fama-French three factors returns, adding the previous default factor and mortgage market factor. See Adam and Guettler (2015).

OD and SD are dummies variables indicating whether the paired funds make opposite trades or same direction trades. Paired funds are not directional-related if both OD and SD are equal to zero. $abs[\Delta\beta_{(ij)t}]$ is the absolute value of fund level control differences. Control variables included are fund pair differences of fund TNA, flow, age, institutional, investment grade, expense ratio, and turnover ratio. δ and γ are time and fund pair fixed effects, respectively. We report the estimation results in the following table.

[Table 2.5 about here.]

We observe from column (1) to column (5) that funds take opposite directional trades within the family exhibit significantly different performances. For example, fund pairs have performance difference of 0.38% in terms of quarterly 5-factors alpha if one of the fund is purchasing naked CDS while its peer purchase the underlying bond of the very CDS. The results confirm our conjecture that cross-fund strategies do exist and fund family level concerns in trading CDS dominate in-family fund tournament. However, in the untabulated follow-up analysis, we do not find consistent support that families aim to create star funds at the cost of their peers in facilitating cross-fund CDS trades[50].

2.B Appendix B: The Determinants of the CDS Strategies: The Multinomial Approach

The definitions of the CDS strategies are interdependent. We therefore employ the multinomial logit model in this appendix to further confirm the determinants of the defined CDS strategies. We define the categorical dependent variable "strategy" as

[50] We further decompose the OD dummy to indicate the CDS trading party and the underlying trading party (OD_CDS and OD_U). We hypothesize that the CDS trading party (that take a naked long CDS position) would hedge for the underlying party's position for family value purposes. This would incur a cost to the CDS trading party. In panel regressions on fund quarter level with fund performance (returns and alphas) as the dependent variable, we find OD_CDS funds do exhibit inferior performance. However, OD_U does not have consistently significantly positive coefficient.

the dominant CDS strategy of each fund quarter, since multiple CDS strategies can be entered into in one fund quarter[51]. The relevant marginal effects on the determinants with multinomial logit are reported in the following table.

[Table 2.6 about here.]

The multinomial analysis produces consistent predictions in terms of the effect of manager characteristics on CDS strategies. Manager age, experience and education are positively correlated with short CDS strategies. Female managers hedge more than male managers. However, there are a few notable differences comparing with Table 2.4. Investment grade funds are not more likely to hedge with the current specification. Turnover ratio and expense ratio are insignificant in explaining the strategies.

[51] An alternative way of executing the multinomial model would be to analyze the determinants on CDS issuer level. For each issuer quarter, CDS strategies are mutually exclusive. The marginal effects on the determinants are very similar to those described in this appendix with the dominant CDS strategy approach. We therefore skip the issuer level study but the results are available upon request.

Table 2.1: Sample Summary Statistics

The table shows the fund, manager and CDS issuer summary statistics. The sample covers top 100 U.S. fixed-income mutual funds with a period from 07.2004 to 12.2010. Panel A is on fund quarter level, while Panel B is on issuer quarter level. The definitions of top 100 funds and fixed-income funds are as given in Section 2.2. Quarterly Flow is calculated by $[TNA_t - TNA_{t-1}(1 + r_t)]/TNA_{t-1}$.Institutional is the fraction of fund TNA held by institutional investors. Investment Grade is a dummy variable that equals to one for investment grade funds. Investment grade funds have Lipper classes of one of the following: corporate debt funds A-rated, corporate debt funds BBB-rated, short investment grade, short-intermediate investment grade, intermediate investment grade. Manager Exp is the number of years the manager worked for top 100 funds. Manager Age and Manager Exp are average values of the team. Top20 Uni is a dummy variable indicating at least one of the team member graduated from one of the top 20 universities. Master and Ph.D. are dummy variables that equal to one if at least one of the team members attained such degrees. Female is a dummy that equals to one if there is at least one female manager in the team. Counterparty Risk (1 Year) is the one year default probability of the counterparty investment bank. CDS Basis is the difference between CDS market spread and z spread as provided by Bloomberg. Bond Liquidity is the difference between ask z spread and bid z spread. CDS Basis, Bond Liquidity and Z spread are measured by the issue with 5 years to maturity or closest to 5 years to maturity.

Variable	**N**	**Mean**	**Median**
Panel A: Fund Level			
TNA(ln)	2557	7.9091	7.7466
Fund Age(ln)	2557	2.9798	2.9957
Expense Ratio	2557	0.7712	0.7411
Turnover Ratio	2557	1.4122	0.8200
Quarterly Flow	2533	-0.0015	-0.0054
Institutional(%)	2557	0.3338	0.1251
Investment Grade	2557	0.6117	1.0000
Manager Age	2366	44.1117	43.0000
Manager Exp	2555	2.5766	2.2000
Top20 Uni	2557	0.5487	1.0000
Master	2557	0.4258	1.0000
Ph.D.	2557	0.0919	0.0000
Female	2549	0.1844	0.0000
Panel B: Issuer Level			
Counterparty Risk (1 Year)	15649	0.0199	0.0090
CDS Basis	14995	-69.0158	-34.9590
Bond Liquidity	9768	11.1322	3.1621
Z Spread	14995	494.1673	236.0290

Table 2.2: The Definitions of CDS Strategies

The table summarizes the CDS strategies defined in Section 2.3. For all definitions the bond notional refers to the notional of the underlying bond that is matched to the CDS. In the strategy hedging, over-hedged positions are included. In the strategy speculating via short CDS, if there is no corresponding underlying bond position in the current quarter then the strategy is defined as outright CDS.

Strategy	**Definition**
Negative Basis Trading	Δbond notional$_t \approx \Delta$long CDS notional$_t > 0$ and CDS basis$_t \leq -10$
Hedging	Δlong CDS notional$_t > 0$ and bond notional$_t \neq 0$ and bond notional$_{t-1} \neq 0$ and Nbasis$_t = 0$
Speculating via Naked Long CDS	Δlong CDS notional$_t > 0$ and bond notional$_t = 0$ and SIC $\notin [6000, 6999]$
Bond Synthesizing	$\lvert\Delta$short CDS notional$_t\rvert > 0$ and basis$_t > 0$ and CDS Liquidity is Better
Speculating via Short CDS	$\lvert\Delta$short CDS notional$_t\rvert > 0$ and basis$_t \leq 0$ and Bond Liquidity is Better

Table 2.3: Number of Issuer Level Cases in Each CDS Strategy

The table summarizes the issuer level CDS strategies defined in Section 2.3. The sample covers the top 100 U.S. fixed-income funds for the period 07.2004 to 12.2010. For all definitions the bond notional refers to the notional of the underlying bond that is matched to the CDS. In the strategy hedging, over-hedged positions are included. In the strategy speculating via short CDS, if there is no corresponding underlying bond position in the current quarter then the strategy is defined as outright CDS.

CDS position change	**Case count**	**Strategy**	**Case count**
Increasing long	1724	**Negative basis trading**	432
		Hedging	238
		(Over-Hedged)	81
		Speculating via Naked Long CDS	781
Increasing short	2100	**Bond Synthesizing**	597
		Speculating via Short CDS	1503
		(Outright CDS)	912
Decreasing long	319		
Decreasing short	766		

Table 2.4: The Determinants of the CDS Strategies

The table presents the determinants analysis of CDS strategies involving fund and manager characteristics in a panel logit setting. The regressions are on fund quarter level. The dependent variables are dummy variables indicating CDS strategies as defined in Section 2.3. The strategy dummies are collapsed to fund quarter level and are assigned a value of one as long as there is at least one case of the strategy in the fund quarter. The construction of all fund and manager characteristics, as well as a summary statistics table for these variables, are provided in Section 2.2. In each cell the reported are marginal effects and t statistics. All standard errors are clustered at fund level. In all columns time dummies are included.

	(1) N.Basis Trading	(2) Hedging	(3) Speculating Naked Long	(4) Bond Synthesizing	(5) Speculating Short
TNA(ln)	0.114***	0.0982***	0.0847*	0.110	0.0580
	(10.87)	(7.34)	(1.77)	(0.48)	(0.93)
L1.Alpha5F	0.323	0.0449*	0.331	0.113	-0.271
	(0.58)	(1.81)	(0.39)	(0.20)	(-0.28)
Fund Age(ln)	-0.00170	0.00568	-0.0897	-0.113**	0.0468
	(-0.04)	(0.16)	(-1.37)	(-2.51)	(0.75)
Institutional(%)	-0.0258	-0.0241	0.00501	-0.0211	0.0168
	(-0.59)	(-0.43)	(0.06)	(-0.35)	(0.31)
Investment Grade	0.111	0.0502**	0.0615*	-0.171	-0.093***
	(1.31)	(2.13)	(1.82)	(-0.52)	(-2.99)
Turnover Ratio	0.0156*	0.000236	0.00182	0.0354**	0.0391***
	(1.76)	(0.02)	(0.10)	(2.18)	(4.18)
Expense Ratio	0.00540	0.127	0.307**	0.228*	0.185
	(0.07)	(1.41)	(2.04)	(1.87)	(1.59)
Top20 Uni	-0.00843	-0.0433***	0.164***	0.137***	0.142***
	(-0.29)	(-3.19)	(3.03)	(2.89)	(3.83)
Master	-0.0546**	-0.0363***	0.0840	0.218***	0.127***
	(-2.02)	(-3.57)	(1.02)	(5.12)	(2.88)
Ph.D.	-0.180***	-0.0674	0.0621	-0.129	-0.0277
	(-2.59)	(-0.98)	(1.18)	(-0.92)	(-0.22)
Manager Age	-0.00400	-0.00683**	-0.000699	0.000678**	0.00448*
	(-1.58)	(-2.16)	(-0.17)	(2.11)	(1.82)
Manager Exp	-0.00721	-0.0424***	-0.0261	0.00171	0.00516***
	(-0.41)	(-2.87)	(-1.01)	(0.10)	(4.27)
Female	0.0788**	0.174***	0.0960***	0.0670	-0.156
	(2.48)	(4.09)	(3.27)	(0.85)	(-0.78)
Observations	2277	2277	2277	2277	2277
Pseudo R^2	0.1611	0.1032	0.1159	0.0813	0.1153
Time Fe	Yes	Yes	Yes	Yes	Yes
Clustered Std	Fund	Fund	Fund	Fund	Fund

Marginal effects; t statistics in parentheses

(d) for discrete change of dummy variable from 0 to 1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: Trade Directions and Fund Family Level Concerns

The table presents fund performance differences between fund pairs when same direction or opposite direction trades are undertaken as proxied by naked CDS trades and their matched underlying trades in other funds in the fund family. The regressions are facilitated in a panel setting with fund pairs (within fund families in each quarter) as the panel variable. The dependent variables are absolute values of performance differences. Fund performance is measured by raw return, 1-factor alpha, 3-factors alpha, 4-factors alpha and 5-factors alpha as described in the text. OD is a dummy variable that equals to one if one of the funds is taking a naked long CDS position while its matched peer in the family hold the underlying of the CDS. SD is a dummy variable that equals to one if one of the funds is taking a naked short CDS position while its matched peer in the family hold the underlying of the CDS. Control variables included in the regressions but are not shown are fund pair differences of Fund TNA, Age, Institutional, Investment Grade, Expense Ratio, and Turnover Ratio. In each cell the reported are coefficients and t statistics. All standard errors are clustered at panel variable level. In all columns time dummies and fund pair dummies are included.

	(1) $\lvert\Delta$Fdret$\rvert$	(2) $\lvert\Delta$Alpha1F$\rvert$	(3) $\lvert\Delta$Alpha3F$\rvert$	(4) $\lvert\Delta$Alpha4F$\rvert$	(5) $\lvert\Delta$Alpha5F$\rvert$
OD	0.00199***	0.00428***	0.00387*	0.000583**	0.00381***
	(4.01)	(3.60)	(1.90)	(2.22)	(8.64)
SD	0.0000283	-0.00321**	0.00812***	-0.00304***	-0.000944
	(0.68)	(-2.07)	(5.11)	(-2.98)	(-0.70)
Observations	38625	38601	38625	38601	38556
R^2	0.007	0.236	0.290	0.126	0.309
Adjusted R^2	0.006	0.236	0.289	0.126	0.309
Controls	Yes	Yes	Yes	Yes	Yes
Fund Pair Fe	Yes	Yes	Yes	Yes	Yes
Time Fe	Yes	Yes	Yes	Yes	Yes
Clustered Std	Fund Pair	Fund Pair	Fund Pair	Fund Pair	Fund Pair

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: The Determinants of the CDS Strategies: The Multinomial Approach

The table presents the determinants analysis of CDS strategies involving fund and manager characteristics in a multinomial logit setting. The regressions are on fund quarter level. The dependent variables is a categorical variable indicating the dominant strategy of the fund quarter. The construction of all fund and manager characteristics, as well as a summary statistics table for these variables, are provided in Section 2.2. In each cell the reported are marginal effects and t statistics. All standard errors are clustered at fund level. In all columns time dummies are included.

	(1) N.Basis Trading	(2) Hedging	(3) Speculating Naked Long	(4) Bond Synthesizing	(5) Speculating Short
TNA(ln)	0.0111***	0.000349	0.0189*	0.0136*	0.00776
	(2.66)	(0.08)	(1.76)	(1.92)	(0.96)
L1.Alpha5F	0.0171	0.0130	-0.0830	-0.308*	0.101
	(0.12)	(0.18)	(-0.43)	(-1.72)	(0.38)
Fund Age(ln)	0.0178	0.0301	0.0227	0.00392	0.0323
	(0.87)	(0.65)	(0.80)	(0.18)	(1.42)
Institutional(%)	0.00348	0.0159	0.0271	0.0506**	0.0259
	(0.38)	(1.41)	(0.73)	(1.98)	(0.98)
Investment Grade	-0.0209**	-0.00363	0.0549	-0.0320	-0.0526**
	(-1.98)	(-0.46)	(1.53)	(-1.15)	(-2.54)
Turnover Ratio	0.00151	-0.00739	-0.00610	0.00628	0.0126**
	(0.73)	(-0.74)	(-0.98)	(0.87)	(2.41)
Expense Ratio	-0.0166	-0.0211	-0.00238	0.00725	0.0448
	(-1.20)	(-1.05)	(-0.04)	(0.21)	(1.27)
Top20 Uni	-0.0100*	-0.00583	0.0680***	0.0347***	0.0857***
	(-1.72)	(-0.80)	(3.07)	(3.58)	(4.01)
Master	-0.0116**	-0.0108***	0.0376	0.277***	0.0982***
	(-2.07)	(-3.66)	(1.37)	(3.78)	(2.92)
Ph.D.	-0.182***	0.00551	0.0543**	0.00281	-0.0157
	(-4.50)	(0.45)	(2.28)	(0.05)	(-0.41)
Manager Age	-0.000963*	-0.00135**	0.000552	0.00108***	0.00288**
	(-1.84)	(-2.24)	(0.40)	(4.13)	(2.15)
Manager Exp	-0.00190	-0.00109	-0.00291	0.00949**	0.00329***
	(-1.05)	(-0.80)	(-0.61)	(2.35)	(3.73)
Female	0.0137**	0.102***	0.0477***	-0.0209	-0.0702
	(2.51)	(4.36)	(3.20)	(-0.73)	(-1.24)
Observations	2277	2277	2277	2277	2277
Pseudo R^2	0.2382	0.2382	0.2382	0.2382	0.2382
Time Fe	Yes	Yes	Yes	Yes	Yes
Clustered Std	Fund	Fund	Fund	Fund	Fund

Marginal effects; t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

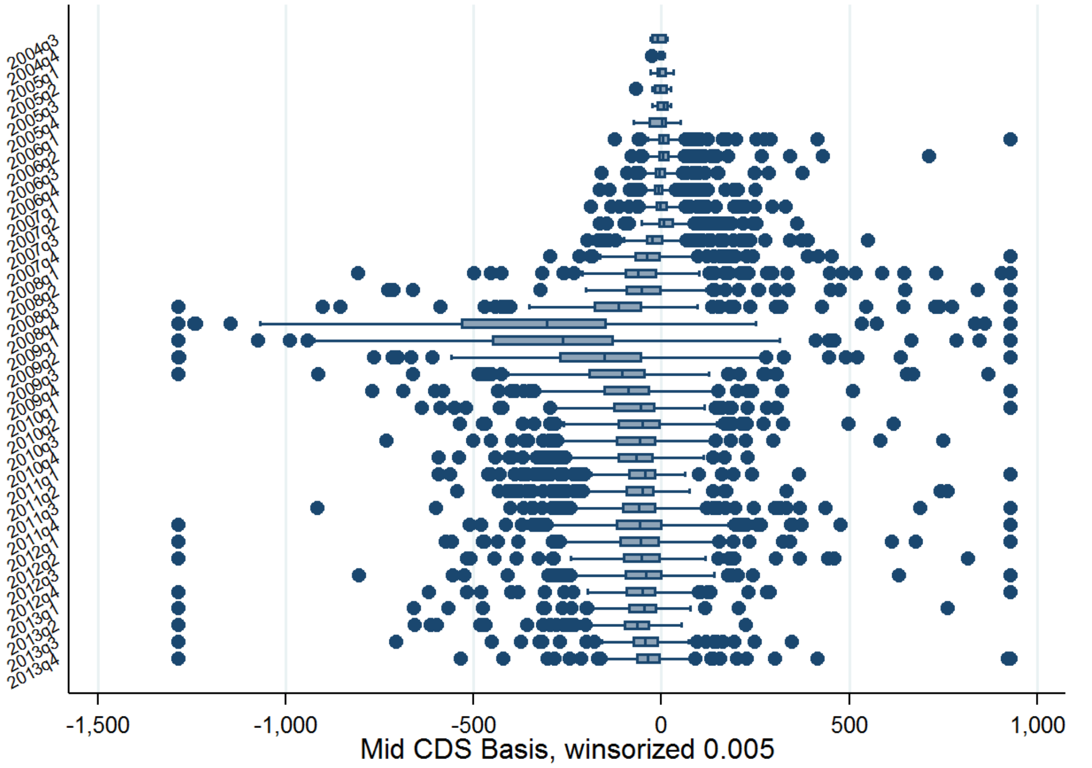


Figure 2.1: The Time Series Distribution of CDS Basis

The graph depicts the distribution (box plots) of quarterly average of weekly CDS basis for the sample CDS contracts over time. The CDS basis is on issuer level with 5 years to maturity (or the closest). The basis, displayed on the x-axis, is calculated as the difference between market CDS spread and z spread. In each quarter the shaded box contains CDS basis that lies within the 25th percentile (Q1) to 75th (Q3) percentile range, with the vertical solid line in the each box denote the median (Q2). The adjacent lines are determined by $[Q1 - 1.5(Q3 - Q1), Q3 + 1.5(Q3 - Q1)]$. The solid dots are outliers.

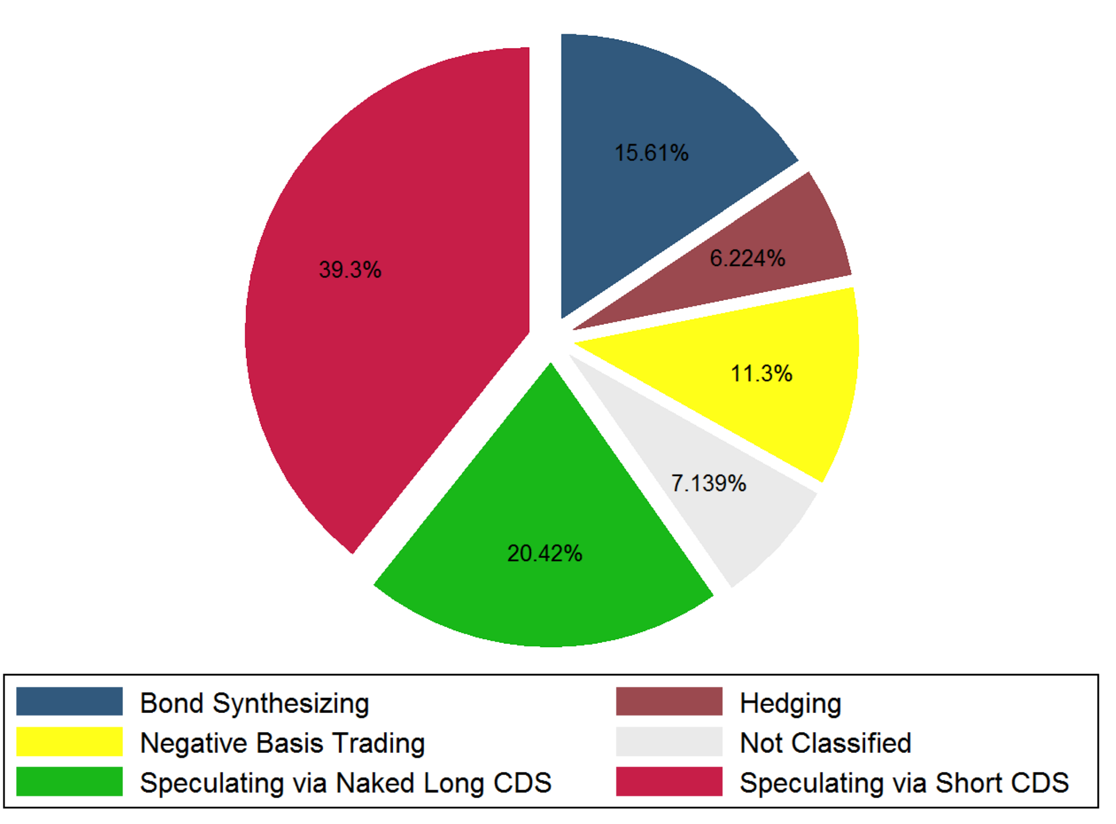


Figure 2.2: Percentage of Issuer Level Cases in Each CDS Strategy

The graph depicts the percentage of each CDS strategy's issuer level case counts within the scope of 1724 long single-name CDS increases and 2100 short single-name CDS increases. The category "not classified" refers to increases in long single-name CDS and is not classified as negative basis trading, hedging or speculation via naked long CDS. The sample covers the top 100 U.S. fixed-income funds for the period 07.2004 to 12.2010. All CDS strategies and their use of thresholds are as defined in Section 2.3 and are on issuer level.

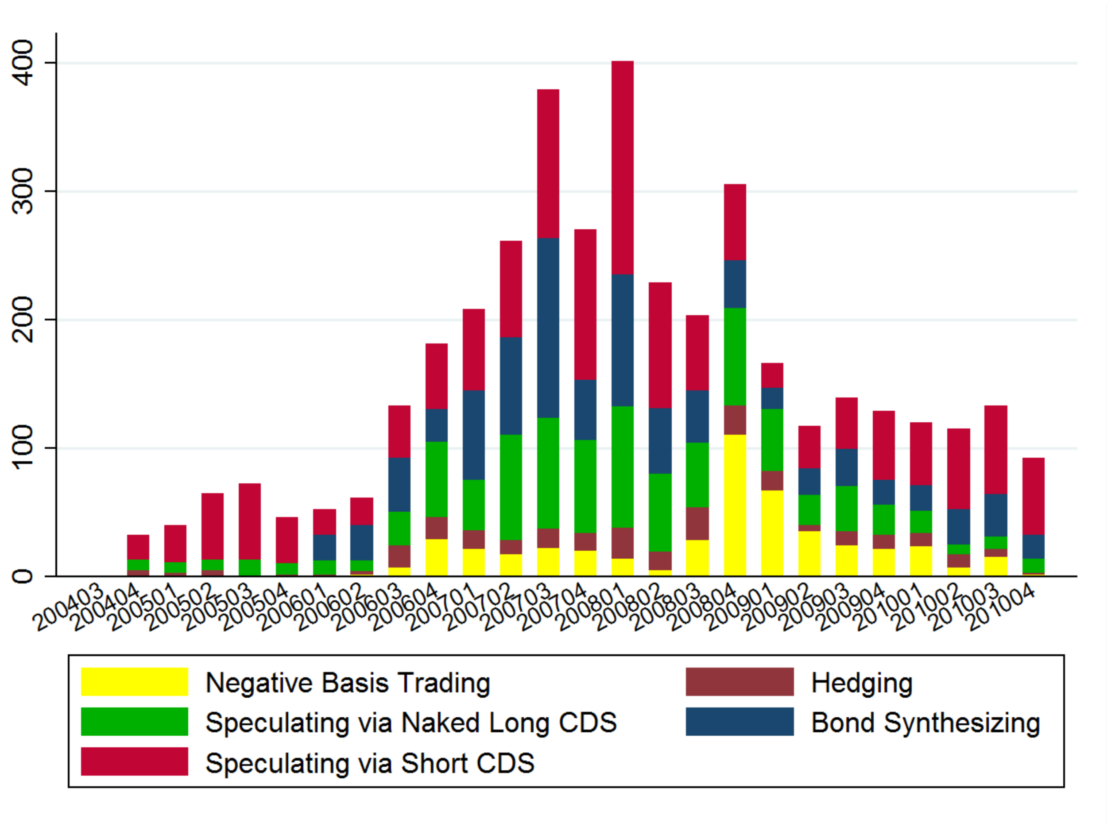


Figure 2.3: The Time Series of CDS Strategies

The graph shows the time series development of the number of cases in each defined CDS strategy category. The sample covers the top 100 U.S. fixed-income funds for the period 07.2004 to 12.2010. All CDS strategies and their use of thresholds are as defined in Section 2.3 and are on issuer level.

Chapter 3

Tail Risk, Fund Performance and Credit Derivatives Trading: Evidence from the Lehman Collapse

Abstract

This study provides a comprehensive overview of the credit default swaps (CDS) investments by the universe of U.S. mutual funds, corporate bond funds in particular. Employing the collapse of Lehman Brothers and the resulting sudden closures of CDS positions as a natural experiment, we find funds on average load up on a significant amount of tail risk by trading CDS. While CDS users benefit when market conditions are favorable, they suffer during periods of clustered defaults. Funds forced to unleash their Lehman CDS contracts exhibit persistent inferior performance in the post-crisis period comparing with their matched peers. However, their immediate losses result from fund outflows were offset by the reduced obligations to fulfill in the crisis period.

Keywords: Mutual funds, Credit default swap, Lehman collapse, CDS counterparties, Fund performance, Tail risk

JEL classification: G11, G14, G23, G28, G33

> History doesn't repeat itself, but it does rhyme.
>
> *(most commonly attributed to) Mark Twain*

3.1 Introduction

In this paper we study the use of credit default swaps (CDS) by the universe of U.S. mutual funds from 2006 to 2014, a much broader sample than those used in the previous literature. In particular, we investigate the scope of CDS use by mutual funds, their incentives in using CDS, as well as the resulting risk and performance implications. Bank of International Settlement (BIS) estimated the total notional amount of CDS outstanding as 9.857 trillion as of the end of 2016[1]. CDS is an agreement between two parties (CDS buyer and CDS seller) under which the CDS seller agrees to compensate the CDS buyer in the event of a loan default (or other credit event) for which the seller receives a premium. The size of this highly controversial market is now comparable to that of in the 2005, and is only a fraction of its almost 60 trillion peak during 2007-2008 just before the global financial crisis. This is not surprising given the higher level of awareness of risk involved in CDS, as well as the public perception that CDS helped fuel the crisis. Global leaders joined forces to reform this market by improving its transparency and price competitiveness, for example by the introduction of central clearing and swap execution facilities. These reforms are incorporated in the Dodd-Frank Act in the United States.

According to the BIS data, we observe the notional amounts of CDS outstanding have been relatively stable since 2015. Moreover, there is a visible discussion on the use of

[1] Bank of International Settlement derivative statistics [`http://stats.bis.org/statx/srs/table/d10.1`, visited on 09.06.2017]

"Bespoke Tranche Opportunity" (BTO). While BTO works in a very similar way as collateralized debt obligations (CDO), it is highly customizable and the existence of debt obligations are not required. With low volatility in credit markets and high prices for corporate bonds, the demand of this completely over-the-counter (OTC) traded, unregulated security, CDS BTO[2], has been increasing significantly. Comparing with the 10 billion issuance in 2015 and the 15 billion in 2016, the new issuance of this security reached 30 billion for the first 7 month in 2017[3]. Therefore, it is important that we revisit the lessons learned from the crisis, and review the role of CDS in funds' investment portfolio.

According to the requirement of the U.S. Securities and Exchange Commission, the SEC, all mutual funds have to file their portfolio holdings periodically[4]. From these reports we identify 768 CDS using funds in the sample period, among which 430 are fixed income funds. CDS is predominantly used by bond funds especially viewing as a percentage of the total number of funds in each fund category. Therefore we restrict our analysis to fixed income funds throughout the paper.

CDS is redundant in a perfect market since its payoff structure can be replicated by the underlying securities. Oehmke and Zawadowski (2016) propose the rationale of the CDS market as a liquidity device especially when the underlying bonds are fragmented. Jiang and Zhu (2015) and Aragon, Li and Qian (2017) empirically confirm this argument and show funds tend to sell CDS when the synthetic bond market is more liquid than the cash bond market. Jiang and Zhu (2015) also point out the yield chasing incentives by comparing the CDS spreads with the portfolio spreads, and additionally the behaviour story of herding that funds tend to follow PIMCO's lead in CDS investment.

[2]This involves combining a series of CDS, and further cutting the pooled portfolio into slices to fit investors with varying risk appetite.

[3]See Financial Times article Investors pour back into crisis-era credit product by Joe Rennison [`https://www.ft.com/content/c4d815b2-86bc-11e7-bf50-e1c239b45787`, visited on 21.09.2017]

[4]The holding reports have to be filed semi-annually before 2004 in NCSR and NCSR/A reports and afterwards quarterly in NQ and NQ/A reports as well as above mentioned semi-annual reports.

To pin down the performance and risk implications of CDS is challenging. Apart from the concurrent events and missing factors that potentially contaminate the results, the reverse causality that funds decide on their CDS strategy because of performance and risk overlook is a sound argument. We use an exogenous shock during which a significant number of CDS positions were forced closure. Lehman Brothers filed for bankruptcy on September 15, 2008. All CDS contracted with Lehman had to be early terminated. Following the International Swap and Derivatives Association (ISDA) protocol and its master contracts for derivative transactions, which is accepted by virtually all present day CDS trades, CDS contracts with Lehman cease to be effective on September 15, 2008 or shortly afterwards, depending on whether automatic early termination is elected. The positions between Lehman and each of its counterparties are netted, and funds become general unsecured creditor of Lehman (Arora, Gandhi and Longstaff (2012)). Although CDS positions are usually collateralized and enjoy a super-senior status, which means funds may liquidate the collateral Lehman posted to collect their receivables without subject to automatic stay (Bolton and Oehmke (2015)), funds may still suffer from losses given the deep discount of settlement prices following the Lehman bankruptcy. In any case, CDS contracts in which Lehman served as the counterparty were concluded[5].

We employ this natural experiment to classify our treatment and control groups as the shock only affects a subset of funds that contracted with Lehman to sell or purchase CDS prior to its bankruptcy. To the extent that the collapse is not anticipated by funds, and funds that contract with Lehman are not systematically different with those do not, we can have an exogenous shock applied to a randomized sample of funds. In both the control and the treated sample we rule out funds that have significant Lehman exposure other than as CDS counterparty. Because these exposures process a threat to inspecting the real effects of CDS closure. We conduct several robustness checks to show that the

[5]Respective guidelines were posted by ISDA on its website. See item 3 of [http://www.isda.org/companies/lehman/pdf/FAQ-Filing-DLM-9-15.pdf, visited on 22.09.2017] as well as [http://www.isda.org/companies/lehman/pdf/FAQ-Close-out-DLM.pdf, visited on 22.09.2017]

anticipation before the event is unlikely, and the selection issue that funds may opt in to contract with Lehman for spread chasing purposes does not drive our results. There is potentially another concern that funds may switch to other investment banks to rebuild their closed positions, and if they do, the magnitude of the shock is limited. While we keep all switchers in the treatment group as it is (since otherwise there is an additional endogeneity issue), we find the switchers are neither significant in numbers nor implying anything that contradicts our main results.

In contrast to the -2% immediate return post Lehman bankruptcy Aragon, Li and Qian (2017) find on the performance of funds using Lehman as the counterparty, we do not find our treated funds perform significant differently than their matched peers shortly following the event. We confirm this finding in both a multi-period difference-in-difference setting and an event study. We interpret the difference in results as the negative impact due to the loss of reputation is offset by the funds' reduced obligation to fulfill during the period when there is a clustering of defaults, especially given the well documented evidence that mutual funds are on average CDS net sellers (Adam and Guettler (2015), Jiang and Zhu (2015) and Aragon, Li and Qian (2017)). The negative impact is also partially offset by the immediate proceeds collected due to the superior status of swaps and derivatives. In addition, we estimate on a matched sample so that our treated and control funds are similar in terms of the extend of CDS use[6] and fund characteristics before the event. We find the treated funds underperform significantly over the long run. We rule out the possibility that it is only reputation loss that drives our results by constructing a secondary match using both pre- and post-bankruptcy data. There is no evidence that funds that contracted with Lehman exhibit different performance than those that do not with similar fund characteristics and number of CDS positions for the

[6]We require a fund to have significant number/portion of Lehman CDS in order to be qualified as treated, so that our treated and matched control funds tend to be heavy CDS users. The likelihood of our treated funds to benefit from the closure of Lehman CDS positions for the period with high amount of defaults following the bankruptcy is therefore even higher than those funds that use Lehman as a counterparty as defined by Aragon, Li and Qian (2017).

entire sample period. We conclude that the closure of CDS positions is related to the long run underperformance in the post-crisis period.

These findings are consistent with the following stylized facts that we summarize. Funds use significantly more CDS during periods of high bond spreads or CDS spreads. We do not find high yield funds are heavier CDS users comparing with investment grade funds, yet CDS-using high yield funds on average underperform non-CDS-using high yield funds, which is in contrast to the respective relation with investment grade funds. CDS trades do not seem to improve funds' index tracking ability, however, funds load up on tail risk by entering into this market. Funds benefit from their CDS positions in the pre as well as post crisis sample periods, during which we observe a positive correlation between spreads and fund performance. This effect is reverted in the course of the crisis when CDS users suffer from significant losses, and high spreads are correlated with even worse performance.

Our study is related to several literatures. First, it is directly related to the earlier efforts to derive the risk and performance implications of derivative use in the mutual fund industry. The empirical evidence is mixed in this regard. In a pioneer paper Koski and Pontiff (1999) document while derivative using equity mutual funds have risk exposure and performance similar to nonusers, their changes in risk are less volatile. Johnson and Wayne (2004) test the findings in a Canadian sample and conclude Canadian derivative using equity funds have lower return but higher risks than nonusers, and Canadian derivative using fixed income funds have higher return and higher risks than nonusers. However, these effects are mostly due to warrants. In a more recent study Cici and Palacios (2015) challenge these previous evidences and find that option using equity funds underperform their peers, while hedging was the dominant motivation that effectively lower risk. We add to this literature by inspecting a particular type of credit derivative that potentially provides us with a clean set up to distinguish from risk increasing versus risk decreasing purposes. In addition, we explore a natural experiment to rule out alternative explanations such as concurrent events or reverse causality that could potentially compromise the identification of the research question.

Second, our paper also adds strong empirical support for the literature on tail risk taking of asset management companies. Noting that apart from hedge funds, many other asset management companies have entered into the CDS market, Rajan (2006) pictures the possibility of heightened risk if there is a serious downturn in the market. Since fund managers are evaluated over a relatively short period of time when the outcome of the CDS positions may not materialize, they are incentivized to sell such contracts in order to benefit from the immediate proceeds collected. Therefore, they are effectively selling diaster insurance and loading up on hidden tail risk. The hypothesis is confirmed by Jiang and Kelly (2012) and Gao, Gao and Song (2016) in the hedge fund industry, while Gao, Gao and Song (2016) further differentiate between fund managers that are skilled and unskilled in exploiting rare disaster concerns. We provide direct and clear evidence that mutual fund managers are involved in tail risk taking as well by trading CDS, and their incentives are especially high in CDS with flying spreads.

Third, there is a stream of literature that focuses on mutual fund coordination and competition. On the one hand, due to the well documented convex flow-performance relationship (Sirri and Tufano (1998) and Chevalier and Ellison (1997)), fund families benefit from high variation in their investment strategies across funds (Nanda, Wang and Zheng (2004)) in terms of fund inflows. This "star fund" effect spills over to other funds in the family and lower skilled families are more likely to pursue such a strategy[7]. On the other hand, there is a sizable literature that classifies mutual fund competition

[7]See also Massa (2003) who shows the cross-fund product differentiation in fund families, as well as recent studies that document cross-fund trading, learning and subsidization for example Gaspar, Massa and Matos (2006), Bhattacharya, Lee and Pool (2013), Brown and Wu (2016), Eisele, Nefedova and Parise (2016), and Cici, Jaspersen and Kempf (2017). Evans (2010) analyze family values in the context of incubation. Basak and Makarov (2014) formulate a theoretical framework to study these issues.

as tournaments. Starting with Brown, Harlow and Starks (1996) who record mid-year losing funds are more likely to increase their risk levels relatively to mid-year winners. The authors attribute this finding to manager compensation structure that base salary is based on asset under management. And since the flow-performance relationship is asymmetric (Sirri and Tufano (1998) and Chevalier and Ellison (1997)), mid-year losers have the incentives to gamble for year-end performance and attract fund inflow[8]. There is rationale for funds to load up on tail risk from both a coordination and a competition point of view, i.e. either to create star funds in families, or to gamble for favorable returns. We add to this strand of literature by documenting a subset of mutual funds are engaged in CDS trading due to these incentives.

Forth, our paper is most related to the other three papers that examine how CDS are used by mutual funds, namely Adam and Guettler (2015), Jiang and Zhu (2015) and Aragon, Li and Qian (2017). While the data set we employed is similar to the other papers, we have different research focuses. Adam and Guettler (2015) find that while team-managed CDS using funds outperform single-managed funds, the relationship is reversed during the financial crisis. The authors attribute the evidence to the costs and benefits of team management including more expertise, experience and skills but more coordination problems and longer decision times. Jiang and Zhu (2015) essentially test and confirm the theory of Oehmke and Zawadowski (2015) on the liquidity provision role of the CDS market. They additionally argue that smaller funds follow leading funds in risk taking and mutual funds use CDS also for yield chasing purposes since the average spread of funds' CDS positions is higher than that of their rest of the portfolio. We add to their analysis by pinning down the resulting risk and performance consequences of CDS use, and extend to include multi-name CDS in the analysis. Aragon, Li and Qian

[8]Koski and Pontiff (1999) detail similar behavior specifically targets at derivative use of mutual funds. Kempf and Ruenzi (2007) provide evidence of tournaments within fund families. Some other authors interpret from a manager job security perspective, for example Qiu (2003) and Hu, Kale, Pagani and Subramanian (2011). In a recent paper Evans, Prado and Zambrana (2017) theoretically and empirically report the existence of both competition and cooperation within fund families.

(2017) exam a number of hypotheses related to general CDS use in the industry with a focus on counterparty risk. The authors compare, for those funds that have at least a CDS contract with Lehman with the rest of the funds, the average fund return 15 days following the Lehman bankruptcy on 15th September 2008. A -2% annualized under-performance is documented. We add to this literature by first to have a clearly defined treatment and corresponding matched control group, as Lehman CDS exposure can be a proxy of various missing variables. Second, instead of focusing on the immediate effect due to the loss of reputation, i.e. counterparty risk, we realize there are sudden closures of CDS positions and employ them as a natural experiment to test the effect of CDS use in terms of risk and performance and track it through time. Even the immediate effect shortly following the event can be attributed to three reasons: the loss of reputation or counterparty risk, the reduced obligation to fulfill since mutual funds are on average net short CDS users and there are a cluster of defaults following the event, as well as the immediate proceeds collected due to the super senior status of derivatives.

The rest of the paper is structured as follows. Section 2 presents the testable hypotheses. Section 3 discusses the data sources, sample construction and summary statistics. Panel analyses on the use of CDS and its risk and performance impact are given in Section 4. Section 5 details our identification strategy that addresses the endogeneity problem, model set up and results. A number of robustness checks are provided in Section 6. Section 7 concludes.

3.2 Hypothesis Development

The three papers with detailed CDS holding data of mutual funds (Adam and Guettler (2015), Jiang and Zhu (2015) and Aragon, Li and Qian (2017)) all confirm mutual funds are on average net sellers of CDS. Becker and Ivashina (2015) document yield chasing phenomenon in a sample of insurance companies that they disproportionably bias towards bonds with higher yield and higher CDS spreads within the same credit rating categories. Although Jiang and Zhu (2015) provide evidence that mutual funds' selling of single name CDS has a low correlation with their bond yield chasing behavior, the underlying logic is rather analogous in these two scenarios. In addition, given the tournament hypotheses and the resulting tail risk taking, especially taking into account that CDS sellers will generate immediate cash inflow while their outcomes are not reviled for a period of time that maybe longer than the evaluation horizon (Jiang and Kelly (2012) and Gao, Gao and Song (2016)), it is especially beneficial for funds to trade CDS during the period of high CDS spreads and thus maximize the potential immediate benefit. This trading strategy could potentially be more pronounced for high yield funds since they are usually less constrained in excessive tail risk taking. However, Adam and Guettler (2015) find investment grade funds are more likely to trade CDS than high yield funds. The authors attribute the observation to two effects, a supply effect that CDS written on high yield bonds are less liquid which is dominated by a relative performance effect, that investment grade funds have clustered performance and a small improvement could results in big change in the ranking.

According to Jiang and Kelly (2012) and Becker and Ivashina (2015) yield chasing of hedge funds and insurance companies introduces significant tail risk and systematic risk. CDS selling, and CDS trading more broadly however, can be used for multiple incentives, many of which may not necessarily increase credit risk exposure (Adam and Guettler (2015)). Purchasing CDS can be motivated by hedging existing bond portfolio or trading on basis apart from speculating the default of the underlying, while selling CDS allow synthetic bond positions when the cash bond market is not that liquid. In particular, even speculative short multi-name CDS positions can be a natural hedge against market risk since multi-name CDS is built upon a variety of underlying assets and is more diversified than bond positions alone (Aragon, Li and Qian (2017)). In addition, gaining exposure to CDS written on indices, either on CDS indices or bond indices, may help funds to track their benchmarks. It is an open question whether CDS traders on average load up on tail risk and credit risk, or merely use CDS to hedge or reduce tracking errors. Our first set of hypotheses is therefore related to funds' incentives in trading CDS.

Hypothesis 1a: Funds are on average more likely to trade CDS when the CDS spread is high.
Hypothesis 1b: Mutual funds load up on tail risk in terms of Kelly and Jiang (2014) tail risk measures by trading CDS. Their incentive to increase credit exposure dominates tracking error management considerations.

Regarding the performance implications of CDS trading, on the one hand, consistent with Rajan (2006) and Jiang and Kelly (2012)'s evidences of tail risk taking and the "disaster insurance" argument, we could imagine if mutual funds decided to trade CDS, and if they traded CDS to gain risk exposure, there will be differential effects on mutual fund performance during and outside the "disaster" periods. The mutual fund in-family tournament and coordination stories are reasonable only if funds may indeed benefit from proceeds collected from CDS trading that are otherwise difficult to produce with conventional portfolio holdings. On the other hand, as noticed by Adam and Guettler (2015), mutual funds use CDS for at least the following five incentives: 1. to sell CDS protection to increase credit exposure, therefore effectively to sell diaster insurance in a speculative way; 2. to explore the liquidity benefits in the CDS market and to trade CDS as a synthetic bond position. This would be equivalent to cash bond investments except for the difference in spreads between the cash and synthetic bond markets; 3. to explicitly target at the negative basis[9] by purchasing the CDS and the underlying bond at the same time. Funds lock in profits as long as the basis narrows from entering to

[9] i.e. the spread difference between the CDS and the underlying bond.

exit, or the assumption that the basis will narrow approaching maturity materializes; 4. to hedge credit exposure by purchasing CDS on the bond holdings; and 5. to enter into a speculative long position in which funds only benefit if an event was triggered for the underlying but otherwise lose premium payments. Our second set of hypotheses concentrates on the performance implications of funds' CDS use, taking into account that mutual funds are on average CDS net sellers (Adam and Guettler (2015), Jiang and Zhu (2015) and Aragon, Li and Qian (2017)).

Hypothesis 2a: Comparing with funds not using CDS, CDS users perform better outside the crisis, and worse during the crisis. In addition, CDS users benefit more from their positions outside the crisis when the CDS spread is high, and they suffer more during the crisis when CDS spread is high.

Hypothesis 2b: Comparing with their matched peers, funds with significant CDS positions contracted with Lehman Brothers experience significant underperformance in the post crisis period. The effect is separable from counterparty risk considerations.

Hypothesis 2c: Funds with significant CDS positions contracted with Lehman Brothers do not exhibit significant performance difference after the Lehman bankruptcy during the crisis comparing with their matched peers. This is due to the immediate benefit resulting from a reduction in CDS positions and therefore reduced obligation to fulfill during the period of clustered defaults as well as the immediate proceeds collected are offset by the fund outflow resulted from loss of reputation.

3.3 Data, Sample Construction and Summary Statistics

3.3.1 Data Sources and the Sample

U.S. Mutual funds that fall into the justification of the Investment Company Act 1940 are required by Securities and Exchange Commission, the SEC, to disclose their portfolio holdings quarterly in NQ, NCSR and NCSRS reports[10]. Our primary data source is these SEC filings. We extract from these filings the Series IDs[11] ,CIK, Tickers, Report date (rdate), Filing date(fdate), a dummy variable indicating CDS use, the number of CDS contracts, and the contracted counterparty information[12].

We match the SEC filings data with MFlinks wficn by tickers and fund names. 87% of the funds in the SEC filing universe are matched with a wficn. We further merge the matched database with CRSP mutual fund database using the matches provided by MFlinks in order to retrieve fund level characteristics. Fund flows are calculated using TNA and fund returns following previous literature. We keep wficn as our fund identifi-

[10]The holding reports have to be filed semi-annually before 2004 in NCSR and NCSRS reports and afterwards quarterly in NQ as well as the above mentioned annual and semi-annual reports.

[11]NQ, NCSR, and NCSRS reports keep series IDs as the identifier on fund level. The reports are filed on Fund company level, e.g. PIMCO funds, which is identified by central identification key (CIK). Thus in each report there can be multiple funds filed.

[12]We thank Thomas Verchow for the help in extracting the CDS data. The extraction uses texture analysis technique and follows Adam and Guettler (2015) in identifying CDS strings, including the appearances of the words "Credit Default", "Default Swap", "CDS", "Default Contract", and "Default protection". The extraction starts with dividing the files into subparts of each series ID. CDS keywords are then searched through the subfiles. The next steps are extracting the following in order: tables (text or html) following CDS keywords, header and body of tables, columns, and desired information. After automatically extracting the information we manually inspect 100 randomly selected fund reports from the sample for quality control. Notional amount of the CDS positions, buy and sell directions, underlying information are deemed not of high quality and discarded. The contracted counterparty information is of high quality since there are a limited number of counterparties available, namely major global investment banks. See Appendix A for a list of identified counterparties. For each treated funds we manually check their reports to verify the information of their CDS counterparties. In order to rule out the possibility that some funds that fit our treated definition may end up in the control sample and thus bias our results, for each matched control funds we manually screen for their CDS counterparties. If a control fund fit into the treated definition we put it into the treated and redo the entire matching to generate the new control set. The procedure goes on until all treated and control are screened to be correct. We have only 1 fund that we need to replace.

er[13] and the CRSP mutual fund sample as our universe. In the final sample we have 768 distinct CDS using funds covering the sample period from January 2006 to December 2014. At this stage we keep funds of all types to generate summary statistics but we will narrow to CDS using fixed income funds, which is counted at 430, in our analysis since CDS is only significantly used in this fund category. We keep CRSP objective code as the major fund type identifier to distinguish between fixed income funds, equity funds, money market funds, index funds...etc. We merge Lipper objective code, Strategic insight code and Wberger code (following Fang, Kempf and Trapp (2014)) to enrich the definitions of high yield and investment grade fund. A fund is classified as a high yield fixed income fund if it has a CRSP code of "ICQY", or a Lipper code of "HY" or "MS", or a Strategic insight code of "CHY" or a Wberger code of "CHY". A fund is considered to be investment grade if it fits one of the following: CRSP code of "ICQH", or Lipper code of "A", "BBB", "IID", "SID", "SII", or Wberger code of "CBD", or Strategic insight code of "CHQ", "CGN", "CIM", "CMQ", "CSM".

In order to compute risk and performance measures we obtain bond indices values from Datastream, including "LHAGGBD" "LHYIELD" "LHGOVIN" "LHGNM30"[14]. We additionally acquire credit spreads from Datastream and 10-year BAA corporate bond spread from Federal Reserve of St. Louis data repository.

3.3.2 Risk and Performance Measures

Our risk and performance measures are constructed primarily following Adam and Guettler (2015). In particular, if not otherwise specified all measures are calculated on a

[13] Wficn and edgar series IDs are fund level identifiers and CRSP fund number is on fund class level. We follow previous literature to collapse CRSP data to fund level when necessary by TNA weighted averages.

[14] The four terms stand for Barclay's US Aggregate Bond Index, Barclays US Corporate High Yield Index, Barclays US Government Intermediate Index, and Barclays 30-year GNMA Index respectively.

monthly basis using daily data and a rolling estimation window of three months[15]. Our standard derivation, kurtosis and skewness measures are estimated in the same way as Adam and Guettler (2015), and we summarize the benchmarks we used to construct certain other measures as follows[16].

For the one factor alpha, beta, upbeta and downbeta, we use return on Barclays aggregate index minus the risk free rate, the bond market excess return, as the benchmark return.

For the three factors alpha, we use Fama-French three factors returns as the benchmark returns.

For the four factors alpha, we use Barclays aggregate index return in excess of risk free rate, an equity market excess return as in Fama-French, Barclays Corporate High Yield Index return minus Barclays Intermediate Gov index return that accounts for default risk, as well as a mortgage market factor Barclays GNMA index return minus Barclays Intermediate Gov index return as the benchmark returns.

For the five factors alpha, we use the Fama-French three factors returns, adding the previous default factor and mortgage market factor.

We additionally calculate funds' tracking errors and tail risks in order to add evidence to funds' incentives in trading CDS. Tracking errors are computed as:

$$TE = \sqrt{\frac{SSR}{DFR}} \tag{3.1}$$

[15]We have also constructed quarterly measures without rolling estimation windows, the results are quantitatively similar. In the event studies section, however, we have of course completely different estimation windows.

[16]Our analysis is mostly focused on fixed income funds for which these measures apply.

where SSR is the sum of squared residuals from the factor regressions, and DFR is the respective degree of freedom of the residuals. Therefore with one, three, four and five factors model listed above we can compute one, three, four, five factors tracking errors.

Kelly and Jiang (2014) assume the tail distribution of asset returns follows the characterisation:

$$P(R_{i,t} < r | R_{i,t} < u_t) \propto (\frac{r}{u_t})^{-\alpha_i \varsigma_t} \tag{3.2}$$

where $r < u_t < 0$. $R_{i,t}$ is the stock return, u_t is a tail threshold that is common to all stocks at time t, α is a constant and ς is a time-varying tail variable. The equation essentially states that conditional on exceeding a predetermined threshold, the tail of returns follow a power law distribution. The tail risk is governed by $1/\varsigma_t$ as a higher ς_t shrinks the lower tail of the distribution. Kelly and Jiang (2014) show that by applying Hill et al. (1975)'s power law estimator to the cross section of daily returns in a given month t the tail risk component can be estimated by:

$$\frac{1}{\varsigma_t} = \frac{1}{K_t} \sum_{k=1}^{K_t} \ln \frac{R_{k,t}}{u_t} \tag{3.3}$$

Where K_t is the total number of daily returns in month t across all funds to exceed the preset threshold u_t, which we define as the lower 5% of the daily returns in the cross section. We then compute, for each fund, a tail risk measure for each month. We standardize the tail risk measure in all of our analysis:

$$TR = \frac{\frac{1}{\varsigma_t} - \hat{E}(\frac{1}{\varsigma_t})}{\hat{\sigma}(\frac{1}{\varsigma_t})} \tag{3.4}$$

3.3.3 Summary Statistics and Univariate Analysis

Figure 3.1 presents the time series of CDS using funds in our sample. The general pattern is consistent with those documented in Adam and Guettler (2015), Jiang and Zhu (2015) and Aragon, Li and Qian (2017). The number of CDS using fixed income funds peeked at over 120 during the first three quarters in 2008, followed by a consistent decline. A similar trend is shown for equity funds as well.

[Figure 3.1 about here.]

We additionally observe a few stylized facts. Fixed income funds are predominant users of CDS among mutual funds due to the nature of CDS. The fraction of equity funds with CDS positions is negligible comparing with bond funds, especially considering the equity fund universe is more than 4 times larger than that of bond funds. This is also confirmed in Table 3.1 in which we compute the fraction of CDS using funds in each fund category over the entire sample period[17]. Besides, for funds that are CDS users, we find bond funds on average trade more CDS than equity funds by comparing the 2 graphs in each panel in Figure 3.1. We also notice the total number of funds (both equity and fixed income) experienced a significant dip following the financial crisis, this is consistent with the recent literature on fund liquidation and mergers. The similar pattern is also documented in Investment Company Institute (ICI)'s fact books[18].

[Table 3.1 about here.]

CDS holdings are presented in close to 15% of fixed income fund-quarters. We cannot distinguish high yield funds from investment grade funds in terms of their CDS trading intensity. Interestingly, bond funds with a foreign focus are heavily engaged in the CDS market, although their incentives in trading these positions may differ from other funds as the credit and liquidity environment are distinct. In untabulated results we find the time trend of these percentages in each fund category with major CDS exposure follow closely with the previous pattern depicted in Figure 3.1. Since fixed income funds are predominantly the major players in the field among mutual funds, we focus on these

[17] As shown in Table 3.1, the only equity fund category that has significant faction of CDS users is EDSC, domestic equity commodity sector funds. The fund category, however, has only three funds thus we decide it is not representative of equity funds in general and difficult to research due to the tiny sample size.

[18] See for example 2017 Investment Company Fact Book [`https://www.ici.org/research/stats/factbook`, visited on 02.10.2017].

funds throughout the paper.

We start our analysis by a number of univariate analyses that draw comparative summaries between CDS users and nonusers in terms of their various performance and risk measures. In panel A of Table 3.2 we tabulate the differences in the mean of risk adjusted returns and basic risk metrics between the two group, and test for the significance levels of these differences. CDS users on average exhibit statistically significant higher risk adjusted returns over their CDS nonuser peers. The results are obtained using data of fixed income funds across all sample period from 2006 to 2014. For example, CDS users have on average 0.5% p.a. higher 5 factors adjusted returns over nonusers over 2006 to 2014. The consistency of the results for all fund performance measures strongly suggests the superior performance of CDS users, yet with univariate analyses only we cannot conclude this is due to CDS trading. In contrast to the previous literature on derivative usage in the fund industry in general, we find evidence in line with Jiang and Zhu (2015) and Aragon, Li and Qian (2017) that CDS users on average present higher risk levels especially in terms of return volatility in our analysis.

We further break down the fixed income funds and examine whether the same comparison holds also for high yield funds and investment grade funds in panel B. While investment grade CDS using funds on average outperform 1.4% p.a. during the sample period, high yield funds on average lose value if they used CDS. Adam and Guettler (2015) document that although the average percentage of investment grade funds' junk CDS is higher than their percentage of junk bonds, they are still by far smaller than that of high yield funds. Therefore the opposite performance results for high yield and investment grade funds could be due to the higher amount of losses incurred during the financial crisis when high yield funds were loaded with significant credit risk by trading CDS. Investment grade funds on average have lower return volatility than high yield funds, which is as expected. However, while the standard deviation of CDS using investment grade funds is lower than that of investment grades without CDS positions, the relationship is reversed for high yield funds. This suggests the likelihood of differences in CDS trading motives between investment grade and high yield bond funds[19]. In particular, high yield CDS using funds present significantly higher down beta, which is an indicative evidence that they suffered from more losses during the financial crisis[20].

[Table 3.2 about here.]

We continue the univariate analyses by switching from the entire sample period to a year by year and quarter by quarter analysis in Table 3.3 that serves as a preliminary test for the performance implication of CDS use during the financial crisis. According to panel A of the table CDS users consistently outperform from 2006 to 2014 except for 2008 and 2011. The most economically significant overperformance occurred in 2009 and 2010 during which the market was recovering from the 2008 crisis. The euro zone debt crisis has built up in 2011 and U.S. sovereign rating was downgraded in August of the same year. We see a clear structural break of the performance differential between CDS using funds and other funds during the financial crisis. Since our treated event occurred in September 15, 2008, it is important for us to check in which quarters do the structural break initiate and end. Panel B is dedicated to a quarter by quarter analysis on the same question. We observe a clear structural break in the quarter 2 of 2009, starting from which the CDS users begin to beat their CDS non-using peers before a more than 4.6% p.a. average under-performance was recorded for the CDS using funds in the quarter 1 of 2009.

[Table 3.3 about here.]

We visualize the difference in 5-factors alphas between CDS users and nonusers in Figure 3.2 with two density histograms. In panel A we check the distribution across the entire

[19] Adam and Guettler (2015) find investment grade funds are more likely to trade CDS, but not net short CDS.

[20] In untabulated results we also check how do early CDS users (that start to use CDS in 2006) perform in order to argue whether experiences in previous CDS trading would be an advantage for CDS trading later on. We do not find systematic differences in performance between these funds and other CDS using funds.

sample period of 2006 to 2014. Funds that are not using CDS clearly exhibit higher kurtosis with more risk adjusted returns distributed around the mean, which is consistent with panel A of Table 3.2. CDS users have more alphas distributed at the tails, both the left and the right, suggesting their incentive to trade CDS for yield enhancement, and loading up on tail risk as a result. While CDS nonusers experienced a highly left skewed distribution in 2008 as depicted in panel B, CDS users suffer from even more losses. A significant number of CDS using funds recorded a 5-factors alpha on the far left tail, with minimum amount of right tail distribution comparing with nonusers.

[Figure 3.2 about here.]

3.4 The Determinants of CDS Use and its Performance and Risk Implications

In this section we present our results on the determinants of CDS use, in particular how do CDS and bond spreads, fund type and fund size correlate with the probability to use CDS. We also check whether fund performance and risk are affected by CDS trades, how do spreads and fund types contribute to funds' incentive chasing objective, and how do the landscape change during the financial crisis. In addition, the tracking error management hypothesis is directly contrasted against the tail risk taking motivation.

3.4.1 The Decision to Use CDS

If CDS trading is incentivized by yield chasing and thus effectively analogous to selling disaster insurance (Rajan (2006)), one can reasonably expect funds' decisions to use CDS, as well as the timing of CDS trades to be influenced by CDS as well as bond spreads. CDS spread is directly related to how effective CDS is as a yield chasing device, and bond spread of the underlying converges to CDS spread as maturity is approaching.

Funds may indeed take advantage of the basis between the CDS and the underlying bond market[21], and this is exactly due to the rational expectation that the basis will converge to zero. Therefore, although there could be temporary divergence, bond and CDS basis usually move in similar directions. We formally test for these in Table 3.4.

[Table 3.4 about here.]

The table reports marginal effects from probit regressions using CDS dummy as the dependent variable. Consistent with Adam and Guettler (2015)'s conjecture, larger funds are more likely to trade CDS, with PIMCO total return funds as the most prominent CDS user. Expense ratio and turnover ratio are positively correlated with CDS use as expense ratio is related to the level of sophistication that funds offer, and turnover ratio is a proxy of liquidity needs as adopted in Jiang and Zhu (2015). Fund performance is positive in explaining CDS use, which is not surprising given the univariate result that CDS users on average outperform their peers over the entire sample period. In column (1) we find CDS spread is both statistically significant and economically meaningful in predicting CDS using funds as a 100 basis points increase[22] in CDS spread is correlated with a 7% higher probability of CDS trading. A natural concern is of course this effect maybe driven by time trends, as CDS spreads peaked during the financial crisis, funds also tend to be heavily CDS users especially before the burst. We therefore include time fixed effects in column (2) to address this concern. While we believe it is highly unlikely that the co-movement of CDS spread and CDS use during the financial crisis is unrelated and we should not completely remove this time trend, the effect is not fully absorbed by controlling for time dummies.

In columns (3) and (4) we test the probability for high yield fund to use CDS comparing with other fixed income funds in general. We do not observe high yield funds with more tendency to trade CDS, which contradicts our prior but is in alignment with the

[21]Funds may trade on negative basis, but positive basis trading is difficult since mutual funds are not allowed to take short positions on cash bond.

[22]The mean value of CDS spread is 293 basis points in our sample.

univariate analysis result. We also cannot find strong supportive evidence that spreads in the previous period affect current CDS investment decisions in columns (5) and (6)[23]. In column (7) we test whether funds experience a shift in their CDS trading strategy after the clustering defaults break out. Funds seem to learn from past lessons and have a lower probability of CDS trading after 2008Q3.

3.4.2 How do CDS Trades Affect Fund Performance and Risk

In this subsection we check how do funds perform if CDS were used, especially the differential effect in and out of the crisis period. Fund tracking errors and tail risks are also examined directly in order to infer the motivation behind the CDS trading. We report these findings in Table 3.5 with pooled panel regressions with the following models (for columns (3) and (4))[24]:

$$\begin{aligned}\alpha_{i,t} = {} & \beta_1 CDS_{i,t} + \beta_2 Crisis_t + \beta_3 Spread_t \\ & + \beta_4 CDS_{i,t} \times Crisis_t + \beta_5 CDS_{i,t} \times Spread_t + \beta_6 Crisis_t \times Spread_t \\ & + \beta_7 CDS_{i,t} \times Crisis_t \times Spread_t \\ & + Controls_{i,t} + Const. + \epsilon_{i,t}\end{aligned} \tag{3.5}$$

[23]Interestingly, in results not reported we find bond funds' CDS use during the previous period is correlated with higher current CDS and bond spreads. If yield chasing is the predominant strategy, this may be interpret as benefiting the funds. However, it is not clear whether this predicative power is due to active and intentional market timing or bad risk management.

[24]The correlation between the default factor that we used in 5-factors alpha estimation with BAA 10-year bond spread is 0.0104, while the correlation between the mortgage market factor with the spread is 0.0172.

as well as (for columns (6) and (8)):

$$\begin{aligned} TE/TR_{i,t} &= \beta_1 CDS_{i,t} + \beta_2 Crisis_t + \beta_3 HY_i \\ &+ \beta_4 CDS_{i,t} \times Crisis_t + \beta_5 CDS_{i,t} \times HY_i + \beta_6 Crisis_t \times HY_i \\ &+ \beta_7 CDS_{i,t} \times Crisis_t \times HY_i \\ &+ Controls_{i,t} + Const. + \epsilon_{i,t} \end{aligned} \tag{3.6}$$

[Table 3.5 about here.]

We observe from columns (1) and (2) that while overall CDS use is positively correlated with performance, the relationship reversed during the financial crisis with close to 3% of underperformance for CDS users comparing with nonusers. We further check how CDS spreads affect fund performance for CDS users and nonuser in and out of the crisis. The comparison can be made over two horizons[25]. First, during the financial crisis, funds using CDS give a 2.2% underperformance[26] than nonusers with a 100 basis points increase in the CDS spread. However, in absent of the crisis CDS using funds, comparing with CDS nonusers, benefit from higher CDS spreads with 3.3% higher alpha for 100 more basis points of the spread. Second, for funds with CDS positions, a 8.3% underperformance[27] is documented during the crisis with 100 basis points higher CDS spread comparing with the non-crisis period with the same amount of change in the CDS spread. To conclude, CDS users benefit substantially from higher CDS spreads with normal market conditions, but suffer from high spreads during the financial crisis, which suggests funds are indeed loading up on tail risk and selling disaster insurance.

Columns (5) to (8) test directly the tail risk taking hypothesis and contrast it with

[25] We use three way interactions as it made possible to test our hypotheses. For example, the differential effect of spreads on performance for CDS users and nonusers during the crisis is given by the coefficient of CDS × CDSP. However, without a three way interaction term the differential effect of spreads on performance for CDS users and nonusers out of the crisis period is also given by the term CDS × CDSP. We therefore check the second differences by including the term CDS × Crisis × CDSP.

[26] This is computed as $(0.000325 - 0.000541) \times 100$.

[27] This is computed as $(-0.000284 - 0.000541) \times 100$.

the tracking error management incentives. Given the significant portion of short multi-name CDS positions written on CDS indices, bond indices and asset backed securities, funds may potentially use the instrument to diversify or to track their intended indices. Not surprisingly larger funds on average have lower tracking errors and Kelly and Jiang (2014) tail risk. Funds have elevated values for these two terms during the financial crisis. We find little support for the tracking error management hypothesis. On the one hand, tracking errors do not appear to be properly managed by trading CDS as CDS users exhibit significantly higher tracking errors. On the other hand, directly measuring tail risk shows CDS using funds indeed have more far-left tail returns, with around 3% higher standardized tail risk, and this value is more than doubled during the financial crisis. High yield funds have significantly higher tail risk during the crisis than other funds, but there is no affirmative evidence the effect is due to high yield funds' trading of CDS.

We test how fund risk measures of Adam and Guettler (2015) are related to CDS use. The results are reported in Table 3.6. With an average fund return standard deviation of around 0.002, being a CDS user in general increases return standard deviation by 5.9%, and during the financial crisis by 14.1%. CDS users also have fatter double tails and are more left skewed. These effects are both statistically significant and economically meaningful, and they hold for both normal periods and crisis periods, with more extreme risk levels during the financial crisis.

[Table 3.6 about here.]

3.4.3 A Two Stage Least Squared Approach

Following the literature on the cross fund learning and information diffusion within the fund family[28], it is reasonable to assume the CDS use could spread across funds within

[28] For example, Cici, Jaspersen and Kempf (2017) document the speed of information diffusion increase fund performance due to higher informational precision.

families. Familiarity and experiences in trading CDS are likely correlated with actual CDS use. In an effort to partially address the endogeneity concern, we therefore employ CDS use of *other* funds within the family for each fund quarter as an instrument, together with other independent variables in the first stage regression to predict funds' probability to use CDS. In particular, for each fund quarter we survey whether *other* funds in the family are using CDS in that quarter. In the second stage we implement the predicted probability of CDS use and regress outcome variables on this predicted value and other independent variables. Although family level coordination and competition are possible, it is not clear how other funds' use of CDS would affect current funds' performance and risk[29]. We report the relevant results in Table 3.7. Notice the first stage is omitted yet its Kleibergen-Paap rk LM statistic is reported[30].

[Table 3.7 about here.]

We test the validity of the instrument by checking the first stage Kleibergen-Paap rk LM statistic[31], which is 97.869 and shows high relevance of the instrument employed. The decision to use CDS of other funds in the family meaningfully affect current funds' probability to trade CDS. Both qualitatively and quantitatively similar results are observed for the second stage regression comparing with Table 3.5 and Table 3.6 without the instrumented first stage[32]. CDS users on average overperform, but reported more losses during the financial crisis. They exhibit higher tracking errors and tail risk, which is likely to suggest the tail risk taking incentive dominates the needs to manage tracking errors with CDS.

[29]It can be argued that other funds use of CDS affect current funds' performance not through current funds' probability to use CDS but through other funds' performance. However, there is little evidence that fund performances within families are harmonized.

[30]In addition to the underidentification test that checks the relevance of the instrument, the correlation between CDS dummy and the instrument is 0.34.

[31]The first stage under-identification LM statistic, as well as other validity statistics are produced with one instrument (CDS use of other funds in the family), one endogenous variable (CDS use) and other independent variables. Interaction terms are not included in the first stage.

[32]With an exception of the coefficient on $Crisis \times CDS$ in the regression with SD as dependent variable. CDS users do not show higher return standard deviation comparing with nonusers during the crisis.

3.5 Identification, Model Set Up and Results

We have so far discussed a number of implications of funds' CDS use. Yet these correlations are to be confirmed with a proper identification. In this section we explore the bankruptcy of Lehman Brothers and the resulting sudden closures of CDS contracted with Lehman as a natural experiment to inspect the causal inferences of funds' CDS use.

3.5.1 The Event

Following the bankruptcy of Lehman Brothers on September 15, 2008, mutual funds that contracted with Lehman Brothers to write or purchase CDS protections have to resolve these positions. While CDS contracts are highly customized and largely unregulated, the standard protocol to follow is set forward by International Swap and Derivatives Association (ISDA). ISDA was chartered in 1985, and since then a common framework and a uniform standard regarding CDS contracting, transaction, among others, have been established. The vast majority of the market participants in the derivatives market now follow the ISDA standards.

ISDA set up master contracts for derivative transactions with detailed protocol to follow when there is default of one of the counterparties. In short, with the default of Lehman, all CDS contracts funds established with Lehman (i.e. so that Lehman was their counterparty, not the underlying) were automatically early terminated. All liabilities of one fund with Lehman are netted, so that the values of each CDS contracts are summed up to a net liability and the CDS contracts cease to be effective[33]. If the net liability of

[33]See for example, ISDA master agreement version 2002, section 6 early termination and closed out netting as well as 6(a) right to terminate following event of default and 6(b) right to terminate following

the funds is negative, they become general unsecured creditor of Lehman. Although as pointed out by Bolton and Oehmke (2015), CDS positions are not subject to automatic stay and therefore there is a possibility for funds to liquidate the collateral Lehman posted in order to collect the receivables if there is any, the market values of CDS are usually tiny comparing with notional or the value exchanged with a triggering event of the underlying[34]. If due to the reasons such as a significant drop in the value of the collateral, funds cannot immediately collect their receivables, then due to the low priority in the claimants and a large number of still ongoing lawsuits, it is highly unlikely that Lehman can fulfill their liability to funds.

Following the standards, CDS positions disappear in the funds' report to the SEC in the immediate quarter following the Lehman collapse. For each of the treated funds that we defined later we manually double check their reports in 2008Q3 to make sure that there is no existence of Lehman CDS contracts, and there is none[35]. Some funds explicitly document the reason for the disappearing of Lehman contracted CDS positions[36].

3.5.2 The Construction of the Treated Sample

The sudden collapse of Lehman Brothers gives us a unique opportunity to exam those funds that face an exogenous disclosure of their CDS positions. In essence, we need the Lehman event to be exogenous to funds, so that funds did not anticipated the collapse and did not actively terminate their contracts with Lehman before the event. The con-

termination event.

[34]While the market values of CDS contracts can be tiny because the CDS contracts are usually initiated such that the value of CDS is zero at the beginning, the payments exchanged between CDS buyers and sellers in an event can be significant.

[35]Other Lehman assets for example Lehman issued securities may still exist after the collapse of Lehman. But any funds that have significant amount of Lehman investments in their portfolio other than CDS are discarded as treated funds as their other Lehman investments may have impacts on fund performance, flow and risk and therefore contaminate our results.

[36]For example, fund with series ID S000000181 stated regarding their CDS position with Lehman as the counterparty: "Contracts were closed upon the declaration of bankruptcy by Lehman Brothers Holdings Inc. on September 15, 2008."

tracts are passively forced to closure after Lehman bankruptcy.

It is unlikely that treated funds have anticipated the collapse of their counterparty before 2008Q3 as otherwise there is less rationale to contract with Lehman to start with, or they should have closed their CDS contracts with Lehman before 2008Q3. The treated funds are defined as those have at least 10 CDS contracts with Lehman as reported in 2008Q2, or those that have at least 5 Lehman CDS contracts, but at the same time the fraction of Lehman CDS contracts is at least 20% of all their CDS contracts in 2008Q2[37].

While funds are not likely to anticipate the Lehman collapse before 2008Q3, it is possible, however, that funds anticipated the collapse of Lehman some time during 2008Q3. This is likely since Lehman has already gone into trouble during that time[38]. Due to data limitations and the quarterly report frequency, we cannot confirm whether funds actively close their CDS contracts with Lehman before 15th September, or passively do so after 15th September. This possess a potential threat to our identification since funds could close their CDS contracts with Lehman because of better management, corporate governance or risk management. If this is the case, any effects we observe are contaminated by funds' active decision.

We offer three explanations to address this issue. One, If funds worried about counterparty risk and ceased to contract with Lehman actively some time during 2008Q3, then either they were taking a long position and worried about the default of the underlying and the default of Lehman at the same time, so that their losses from the underlying cannot be covered by Lehman, or they were taking a short position and worried about not getting periodic payments. In either case they would try to rebuild their position with some other counterparty. We provide detailed analysis on the limited number of

[37] As the threshold is self-defined we conduct sensitivity analysis for the definitions of treated funds and rule out the possibility that there is qualitatively different results.

[38] Aragon, Li and Qian (2017) provide evidence funds are likely to close existing buy-protection CDS with greater counterparty credit risk.

CDS positions that were rebuilt following the Lehman event in Section 3.6 Robustness checks[39]. If funds were taking a short position and worried about the default of the underlying, then there is less rationale to end their CDS contracts with Lehman if they anticipate the Lehman default since their CDS contracts will be concluded. Question only remains if funds anticipated the default of the underlying but not the default of Lehman. This is highly unlikely given that Lehman was the focus of the market during the time.

Two, although Lehman's situation already deteriorated, the eventual collapse was not the market consensus. In fact, the Lehman stock was traded at almost 10 dollars on 12th September, the Friday before collapse, and was kept a price of more than 15 dollars for the vast majority times during the month with all the restructuring plans, before it dropped to negligible values after 15th September. Similarly, average bond value dropped to less than 9 cents per dollar only after 15th September.

Three, there is empirical evidence suggests that while before Lehman collapsed counterparty risk is priced in CDS prices, it is only after the collapse of Lehman counterparty risk is much more significantly priced (Arora, Gandhi and Longstaff (2012)), which suggests the market awareness of counterparty risk was low before the Lehman event. Although CDS contracts are marked to market. The calculations of periodic payments as well as unrealized gains and losses are based on notional amount, notional price, recovery rate, and coupon (premium) rates[40] , but not counterparty risks.

[39] In our main results we keep the limited number of treated funds that rebuilt their CDS that were contracted with Lehman with some other counterparty, and we keep the limited number of CDS reconstructed. Dropping these funds from the treated sample introduce one additional layer of unnecessary endogeneity as the decision to reconstruct is endogenous. Instead we provide detailed analysis on the specifications of these special funds, and conduct a number of robustness checks to rule out the possibility that these funds drive our results.

[40] The amount that the protection buyer has to pay is calculated as the notional price minus the fraction of price that can be recovered in an event of default. This is due to in an event of default, the protection seller takes the defaulted bond from the buyer and pays buyer the principle. And the seller can recover a certain amount from the defaulted bonds. The recovery rates are updated periodically.

Funds may have other business associations with Lehman Brothers other than as the counterparty of CDS contracts. These business associations are certainly affected by the collapse of the company and thus have potential effects on fund performance, flow and risk. In order to exam a clean effect of the sudden closure of CDS positions, funds that have any other investment with Lehman other than CDS are dropped from the treated fund set. After the screening process we are left with 31 treated funds. CDS contracts are largely collateralized. Problem arises if Lehman rehypothecated the collateral posted by funds to some third party. In that case, given the default of Lehman, the third party seeks the possession of the collateral and the funds become general unsecured creditors and this affect the fund performance. However, this effect is likely to be short lived. Moreover, since the collateral is posted both ways, only the net effect counts, which is likely to be much smaller. No matter whether the CDS contracts are collateralized or not, they have to be terminated and netted following the bankruptcy of one party.

There is, however, potentially a selection issue. Treated funds select Lehman Brothers to serve as their CDS counterparty. And counterparty risk is certainly relevant during this selection. During normal time periods, this is not of great concern. But Lehman's credit worthiness has already deteriorated before its collapse. This affects Lehman's bargaining position when CDS contracts were written. And funds may select Lehman because of favorable rates. Thus being a treated fund may be a proxy for certain fund investment style.

In order to address this concern we define a different treated group among which funds have CDS contracts with Lehman already in 2007Q4. Fortunately among the 31 treated funds, 27 have already contracted with Lehman way before Lehman's financial status is made focus of the market. This different group of treated funds serve as a robustness check and the results we get on fund risk and performance are both qualitatively and quantitatively similar.

In Figure 3.3 we depict the time trend of average number of CDS contracts for the treated funds and all other CDS using funds. Treated funds experience a dramatic decrease in the number of CDS contracts they hold following the Lehman event, and their hesitation lasts for a significant period of time. In contrast, other CDS using funds only slightly step back from CDS after the outbreak of the financial crisis and retain almost the same level of average number of CDS before and after the crisis. The significant drop in the number of CDS contracts allows us to estimate treatment effects on various fund level outcomes.

[Figure 3.3 about here.]

3.5.3 The Construction of the Control Sample

Figure 3.3 observes our treated funds have a natural tendency towards heavy CDS users[41]. The average number of CDS positions per treated fund quarter is more than double than that of other non-treated CDS using funds. Therefore although treated funds experienced a significant dip in CDS use, they are still heavy CDS users comparing with other funds. It is not a fair comparison to check how treated funds behave differently than other funds following the drop in the number of CDS positions. This result is mechanical due to the definition of our treated sample. And heavy CDS users are more likely to be treated, this contrasts the randomization assumption of allocating the treated group.

In order to account for this dispersion as well as other potential covariates that could introduce a bias to our estimation, we construct a propensity score matched sample. We follow common practices and transform the data into wide format to run the following

[41]This is mechanical since when defining treated funds we need them to have significant amount of Lehman CDS and therefore CDS so that the drop in the number of CDS is meaningful. We could, of course, take all funds that have Lehman CDS and compare them with all other CDS using funds, but the fraction of CDS contracts with Lehman accounts for less than 7% of total number of CDS contracts in the sample, thus the effect would be hardly detectable.

probit regression[42] and calculate the propensity scores:

$$
\begin{aligned}
Treated_i = {} & \alpha_1 CDS\_2006Q1_i + \alpha_2 CDS\_2006Q2_i + ... + \alpha_{10} CDS\_2008Q2_i \\
& + \beta_1 Hits\_2006Q1_i + \beta_2 Hits\_2006Q2_i + ... + \beta_{10} Hits\_2008Q2_i \\
& + \gamma_1 FundCha\_2006Q1_i + \gamma_2 FundCha\_2006Q2_i + ... + \gamma_{10} FundCha\_2008Q2_i \\
& + Const. + \epsilon_i
\end{aligned}
\tag{3.7}
$$

where treated is a dummy for treated funds, CDS is a dummy for CDS use for that fund quarter, and Hits is the number of CDS contracts. At this stage we match funds based on their CDS use and fund characteristics before the event. The number of CDS contracts is added in the probit predicting propensity scores so that we have a comparable sample between treated and control in term of the extend of CDS use. The predicted outcomes of this probit regression are used as propensity scores for each fund. Next we generate propensity score matched funds with nearest 5 neighbors. For the 31 treated funds we matched 90 control funds with closest propensity scores[43]. Our further analysis is based on the sample consists of these treated funds and their matched control funds.

3.5.4 Difference in Differences Analysis Set Up and Results

In this subsection we estimate the treatment effects in a difference in differences (DiD) setting. Notice, however, the DiD results should be interpreted with caution since the number of CDS positions per fund for the treated funds continue to decline after the Lehman collapse. The decline is certainly not directly caused by the treatment. DiD

[42] We also calculate the propensity scores using cross sectional probit with the snapshot data in 2008Q2, and using panel probit and then take the average scores for each fund. All of the three methods yield similar final treatment effects despite somewhat different matched pairs.

[43] We also use the nearest 1 neighbor technique, for which we match 25 control funds, 3 nearest neighbors, for which we match 59 control funds, as well as kernel propensity score matching technique, for which we get the weights of each fund. The treatment effects resulting from these different matched control groups are both qualitatively and quantitatively similar and thus omitted.

will capture these effects given the relative long post event estimation period. The DiD results therefore can be taken together with the event study results in the next subsection to get a full picture of the treatment effects[44].

The univariate results in Section 3.3 suggest there is a structural break in terms of the performance of CDS using funds during the crisis. The CDS users perform worse during crisis periods comparing with non-users, but have better performance outside the crisis periods. Therefore we estimate the treatment effect in a DiD setting with a structural break, namely with 2 post treatment periods:

$$\begin{aligned} OutcomeVar_{i,t} = {} & \alpha_1 post\_1_t + \alpha_2 Post\_2_t + \alpha_3 Treated_i \\ & + \beta_1 post\_1_t \times Treated_i + \beta_2 Post\_2_t \times Treated_i \\ & + \gamma_1 FundCha_{i,t} + Const. + \epsilon_{i,t} \end{aligned} \tag{3.8}$$

where *post_1* is a dummy variable that equals to 1 for 2008Q4 and 2009Q1, and *post_2* is a dummy variable that equals to 1 from 2009Q2 on. Treated is a dummy indicating treated funds. β_1 is the DiD treatment effect following Lehman collapse but during crisis. Similarly β_2 captures the DiD treatment effect post crisis.

Since the parallel trend assumption is critical for all DiD estimations, in Figure 3.4 we plot the time series of various performance and risk measures for the treated funds and control funds.

[Figure 3.4 about here.]

As we are estimating using the propensity score matched sample, the treated funds and control funds behave similarly and thus parallel trend is observed before treatment.

[44]The continuous declining CDS per fund for the treated funds is unlikely to be a proof that the treatment effects are reputation story only. If the reputation loss is due to contracts with Lehman, then there is less rationale to decrease it further post event since Lehman contracts are resolved anyways. If the reputation loss is due to the fact that funds hold CDS, it still cannot properly explain the decline. Because even the number of CDS per fund for the treated funds is at its lowest, it is still over three times larger than other CDS using funds.

Moreover, there are consistent differences between the two group post treatment in both their performances and risk levels, and the differences are generally of similar magnitude across time. We present the results of the DiD estimates in Table 3.8.

[Table 3.8 about here.]

The coefficient of the first difference in differences estimator measures the treatment effect during the two quarters following the collapse of Lehman and our treated event: 2008Q4 and 2009Q1. The second difference in differences estimator captures the treatment effect after 2009Q1 when the market started to recover.

In terms of fund performance, we find that with a sudden decrease in the number of contracted CDS, funds experienced both statistically significant and economically meaningful drop in measurable alphas after the financial crisis (period 2). This is consistent with our univariate result which shows funds on average benefit from their CDS trading with normal market conditions. Economically speaking, the sudden drop of CDS positions has led the treated funds to have on average 2.1% lower annualized 5-factors alpha comparing with their matched peers with similar fund characteristics as well as the number of CDS contracts booked before the Lehman event. The decrease is consistent over different alpha measures that appropriately adjust for bond market risk factors. We cannot draw any conclusion regarding the immediate treatment effect on fund performance in period 1 during the crisis. Various alphas give conflicting results and are not statistically significant. It seems treated funds suffered from inferior raw returns for all sample periods after the event.

We confirm our hypothesis that funds using CDS maintain on average higher risk levels. The treated funds with a sudden reduction in their number of CDS contracts have on average 5.8% lower annualized standard deviation[45] of their daily returns comparing with their matched peers in the post crisis period. Apart from the total fund risk, treated

[45]This is computed as 0.000229×252.

funds also have lower systematic risk post crisis as measured by betas. In addition, we cannot find strong evidence that investors react to the fact that the treated funds have to close their CDS positions with Lehman.

3.5.5 Event Study and Results

The DiD approach could be challenged for two reasons. One, it does not provide sufficient time series details on the impact of CDS on fund outcomes during the crisis and afterwards, as the effects of CDS are distinct in the two periods. Two, we observe in Figure 3.3 treated funds and other funds use CDS differently after the event, so that these differences are incorporated in the post event treatment effect. This could potentially be addressed by matching on the CDS use over the entire sample period, yet it is still questionable whether the effect of Lehman collapse and the CDS closures can last for a number of years.

We therefore conduct event study analyses to exam such effects over a relatively shorter period[46] of time around the event, and we are able to compare the differences between treated and control funds on a daily basis, and track it through time. As the average holding period of CDS positions is around 4 quarters, within a limited period of time the effects of sudden CDS closures should be more pronounced.

The definitions of treated and control groups are identical to the previous section. We employ daily return data with an estimation window of [-405, -270][47]. We use the 5-factors model to estimate the estimation window coefficients and the event window abnormal returns[48]. Concerning that the factors may not be representative of the risk levels during the crisis, we also accompany, separately to the 5-factors model, with a

[46]The reduction in the number of CDS is unlikely to cause immediate return reaction as well.

[47]We are of course aware that an estimation window long before the event can be problematic since many could have changed during this time. However, we wish to have an estimation window that is free of financial crisis concerns.

[48]Results are robust to use 4-factors model and so on.

self-defined index that uses the weighted average daily return of all mutual funds in the same fund category as the benchmark return. The time series of cumulative average abnormal returns (CAAR) are reported in Figure 3.5 for the 5-factors model and the defined-index model respectively.

[Figure 3.5 about here.]

Consistent with the results we obtained so far, treated funds significantly underperform in the post crisis period. Treated funds have lower CAAR starting from around 60 trading days after the event, and have 5% lower CAAR over the entire event window. This implies starting from 3 calendar quarters after 15th September 2008, funds that close their CDS contracted with Lehman started to experience underperformance since they benefit less from selling disaster insurance in a non-crisis period. This finding also holds for the specification with defined index as the benchmark. It is not apparent, however, whether there is statistical difference between the treated funds' return and control funds' shortly after the event, which we address in the following Table 3.9.

[Table 3.9 about here.]

While treated funds show less negative return at 10% significance level within the 20 days following the event, there is virtually no difference between the groups of funds in terms of abnormal returns during the (20,60) window. Starting from 60 trading days post event, treated funds on average exhibit 2.6 basis points lower abnormal return per day comparing with control funds, and this result is robust to using the defined index model, with which treated funds also have on average 2.5 basis points lower abnormal return per day that is significant at 5% level.

3.5.6 Funds That Reconstruct the CDS Positions

A valid concern is funds may opt to rebuild their CDS positions with some other counterparty after Lehman's bankruptcy. Given the liquidity of CDS contracts especially those more popular ones written on CDS and bond indices, funds are not likely to have to spend too much effort on rebuilding such positions. This certainly is an endogenous choice. If those funds that choose to reconstruct the positions are special in terms of fund management or investment style, then they could potentially drive our results. If this is the case, we have a serious endogeneity issue[49].

For each treated fund we manually look into their filings to check if any Lehman contracted CDS was rebuilt post event[50]. The 31 treated funds had in total 3193 distinct CDS positions in 2008Q2, among which 1056 were contracted with Lehman Brothers[51]. None of these 1056 positions survived in the 2008Q3 reports. However, 4 out of the 31 treated funds rebuilt in total 40 CDS positions that have identical underlying as the Lehman contracts with some other counterparties. That is, a fraction of roughly 4% of positions were rebuilt. Among these 40 positions, 4 are written on corporate bonds, 12 are on ABX and the rest are written on CDS indices.

96% of the Lehman contracted CDS positions held by treated funds were closed permanently without reconstruction. If it is the 4 funds that rebuilt the 40 positions that drive our results, we should expect them to have consistently inferior performance post crisis since our result indicate treated funds have lower post crisis performance. In contrast, if the rebuilding funds are not special so that our general implication of CDS use apply to them as well, we should expect them to have superior performance post crisis comparing with other treated funds that did not rebuild any positions since the 4 funds can potentially benefit from the reconstructed CDS positions in the post crisis period.

[49] Although we keep those funds that rebuilt in the treated to avoid an additional selection issue, we do not have any insight whether the funds that did not rebuild the positions actively choose not to do so or passively did not react to the closures. Therefore we still have the concern that our results may be driven by a subset of funds' active decision, which is endogenous.

[50] Our primary data set does not contain detailed information of the underlying, for the treated funds we check for these positions manually.

[51] By the definition of treated funds they are heavily Lehman fund users, a much higher fraction of CDS are contracted with Lehman. See Appendix A for a general overview of all counterparties.

We split our treated sample into two groups, the 4 funds that rebuilt, and the rest. In the sample of treated funds, we study the performance and risk implications of the 4 funds that rebuilt their positions. Effectively, our new treated sample is now the 4 funds that rebuilt, and the new control sample is the rest of the original 31 treated funds. We report the results in Table 3.10.

[Table 3.10 about here.]

Funds that rebuilt the CDS positions possess higher performance than those did not in period 2, which makes it impossible to drive the inferior performance our treated funds in the same period. We confirm our hypothesis that funds rebuild the positions benefit from such actions in the post crisis period, and other treated funds that have a reduction in the number of CDS positions have inferior post crisis performance. Our main results, although partially offset by a small number of funds that rebuilt, still show off significant.

We further randomize the 4 funds that rebuild as a placebo test. In Table 3.11 we do not find any significance in the interaction terms. Funds that actually rebuilt indeed benefit in terms of post crisis performance, and funds that did not rebuilt and thus had a more significant dip in the number of CDS positions perform worse comparing with their rebuilding peers, which is consistent with our main message.

[Table 3.11 about here.]

Overall, both the DiD approach and the event study confirm our hypothesis that funds with an exogenous closure of CDS positions perform worse in the post crisis period. Equivalently, CDS users perform better in such periods. We cannot find statistically different performance between the treated and the control for the time periods immediately following the Lehman collapse. Combining with our findings in Section 3.4, we interpret this as the benefit of reduced CDS contracts during the crisis (since as discussed previously CDS users suffer from significant losses during the time), as well as the potential immediate proceeds collected if sufficient collateral is posted, are offset by the fund outflow and reputation loss due to Lehman transactions documented by Aragon, Li and Qian (2017).

3.6 Conclusion

Studying the risk and performance implications of mutual fund's use of CDS is challenging due to endogeneity concerns. Apart from concurrent events and other missing factors that prevent one from establishing causal relationships, the reserve causality that funds may opt to trade CDS in anticipation of future risk and return profiles is also a valid concern. We reduce the level of endogeneity in this problem by utilizing the collapse of Lehman Brothers as well as the resulting sudden closure of mutual fund's CDS holdings with Lehman as the counterparty as a natural experiment. Treated funds are defined as those with sufficient Lehman CDS exposures. Control funds are propensity score matched funds with similar pre-event characteristics as the treated funds but without Lehman exposure.

We employ the greatly enlarged sample-the universe of U.S. fixed-income mutual funds as the subject of research. We find CDS users load up significant tail risk in trading CDS. They perform well outside of the crisis period, but suffer from significant losses during. The two predictions are even stronger with high CDS spreads. The sudden drop of CDS positions in the treated funds introduces on average a 2.1% lower annualized 5-factors alpha comparing with their matched peers post crisis. During the financial crisis, however, there is no statistically different performance observed between the treated and the control.

Our analysis is subject to the drawback that funds may choose to reconstruct their closed Lehman CDS positions. We rule out the possibility that the results are driven by the limited number of reconstruction cases by facilitating a further test within the treated funds. Funds that rebuilt the CDS positions possess higher performance post crisis, which means they cannot drive the inferior performance of treated funds post crisis.

Appendix

3.A Appendix A: List of Identified CDS Counterparties

Although our focused counterparty is Lehman Brothers. We provide here a more comprehensive list of identified counterparties to give a more general picture of CDS trading of mutual funds.

[Table 3.12 about here.]

Notice Lehman Brothers declared bankruptcy, and Merrill Lynch was acquired. Therefore counting the fraction of CDS counterparties before the financial crisis, the two would have been more important. Lehman was the second most frequent CDS counterparty before 2008Q3 with 12.2662% of positions, just falls short after Goldman Sachs (12.5543%).

3.B Appendix B: Placebo Tests

In this appendix we additionally provide several placebo tests to support our identification. We randomly pick 31 funds from the fund sample, calculate their propensity scores to use CDS and match them with control samples as described in Section 3.5. The randomly picked funds need not experience a sudden reduction in the number of CDS positions, and since the matched control sample with similar fund characteristics and number of CDS holdings before the event also need not experience forced closures, we shall expect no statistically different performance and risk to exist systematically post event for the 2 groups of funds. We replicate our analysis in Table 3.8 and report the results below.

[Table 3.13 about here.]

As expected, there is no differences between the treated and their control detectable. We further visualize such comparison with CAAR time series derived from event studies. Employing the similar event study set up as in Section 3.5.5, we plot the comparison in the following graph.

[Figure 3.6 about here.]

The time series of CAAR for the treated and the control are almost identical (vertical comparison). It further proves the underperformance of the real treated funds after the financial crisis is indeed related to our treatment, the sudden closures of CDS positions.

Table 3.1: Mutual Fund CDS Holdings by Fund Type

The table reports the average values of the CDS dummy across all fund-quarters in each specified fund category. They measure the fraction of fund-quarters from which at least a CDS position was observed. The measure also serves as an approximation of the fraction of funds that used CDS in each fund category. Fund categories are defined by CRSP objective codes, Lipper objective codes, Strategic Insight codes and Wberger codes. In particular, fixed income funds are those with a CRSP code starting with "I", equity funds start with "E", and money market funds start with "IM". The fund types in the third column refer to a further breakdown of the corresponding fund types in the first column. High yield and investment grade bond funds definitions follow Fang, Kempf and Trapp (2014). Bond funds with foreign exposure have CRSP codes with first two digits "IF". Commodity sector equity funds are listed separately as they are the only equity funds that have significant CDS trading history and they are defined by CRSP as "EDSC" funds.

<table>
<tr><th>General Fund Type</th><th>Mean of CDS Dummy</th><th>Detailed Fund Type</th><th>Mean of CDS Dummy</th></tr>
<tr><td rowspan="3">Fixed Income</td><td rowspan="3">14.51%</td><td>High Yield</td><td>18.58%</td></tr>
<tr><td>Investment Grade</td><td>19.03%</td></tr>
<tr><td>Foreign Exposure</td><td>19.68%</td></tr>
<tr><td>Equity</td><td>0.98%</td><td>Commodity</td><td>25.00%</td></tr>
<tr><td>Money Market</td><td>1.91%</td><td></td><td></td></tr>
</table>

Table 3.2: Comparing Risk and Performance of CDS Users Versus Nonusers

The table reports the averages of risk and performance metrics for funds in various categories. The risk and performance metrics are as defined in Section 3.3, and they are computed with daily data. Alphas are annualized values. CDS users are funds that hold at least one CDS position at the fund quarter. Panel A documents the relevant data for all bonds funds, while Panel B focuses on the high yield and investment grade subgroups. High yield and investment grade bond funds definitions follow Fang, Kempf and Trapp (2014). P values in the fifth column test for the statistical significance of the economic differences in column 4.

Panel A: Comparative Statistics for Bond Funds

Bond Funds				
	Mean among CDS users	Mean among CDS nonusers	Diff	p
Alpha1F	.0280555	.0198445	-.008211	0.0000
Alpha3F	.0399768	.0327969	-.0071799	0.0000
Alpha4F	.0073872	.0023921	-.0049951	0.0000
Alpha5F	.0581934	.0524833	-.0057101	0.0000
SD	.002529	.0021705	-.0003585	0.0000
Kurtosis	4.251913	4.579245	.3273328	0.0000
Skewness	.1601618	.1924703	.0323085	0.0626
Upbeta	-.0626332	-.0777469	-.0151137	0.0226
Downbeta	.487045	.4891736	.0021286	0.8211

Panel B: Comparative Statistics for High Yield and Investment Grade Bond Funds

Investment Grade				
	Mean among CDS users	Mean among CDS nonusers	Diff	p
Fdret	.0002312	.0002048	-.0000264	0.5159
Alpha1F	.010877	-.0018337	-.0127107	0.0000
Alpha3F	.0524078	.0383121	-.0140958	0.0000
Alpha4F	.0055283	-.008501	-.0140293	0.0000
Alpha5F	.0878593	.074499	-.0133603	0.0000
SD	.0024937	.0026418	.0001481	0.0000
Kurtosis	3.423912	3.368135	-.0557764	0.0000
Skewness	-.0203208	.1122578	.1325786	0.0000
Upbeta	-.0452527	.0010818	.0463345	0.0000
Downbeta	.8440454	.8517122	.0076668	0.0117
High Yield				
	Mean among CDS users	Mean among CDS nonusers	Diff	p
Fdret	.0002202	.0002566	.0000365	0.3628
Alpha1F	.0022606	.0163864	.0141258	0.0000
Alpha3F	.0475528	.0570915	.0095386	0.0000
Alpha4F	-.0119088	-.0090995	.0028093	0.0003
Alpha5F	.0860728	.0894581	.0033853	0.0472
SD	.0032555	.0030977	-.0001578	0.0000
Kurtosis	3.255287	3.247045	-.008242	0.4280
Skewness	-.0381526	-.0551718	-.0170192	0.0002
Upbeta	-.0112053	-.1166042	-.1053989	0.0000
Downbeta	1.033193	.9204176	-.1127755	0.0000

Table 3.3: Comparing the Performance of CDS Users Versus Nonusers as Time Series

The table reports the averages of 5-factors alpha for bond funds that with and without CDS positions. The alpha are annualized and are as defined in Section 3.3. CDS users are funds that hold at least one CDS position at the fund quarter. Panel A documents the comparison from 2006 to 2014 year by year, while Panel B focuses on the global financial crisis period with a quarter by quarter recording.

Panel A: Comparative Statistics for Bond Funds: Year by Year Analysis

Bond Funds								
Mean of Alpha5F								
	2006	2007	2008	2009	2010	2011	2012	2013
CDS users	.0472893	.0179483	-.0466584	.0880462	.1006964	.0618575	.0830287	.0170888
CDS nonusers	.0383348	.0089252	-.033558	.0633369	.0770087	.0686823	.0764292	.0089122
Diff	-.0089545	-.0090231	.0131004	-.0247093	-.0236877	.0068248	-.0065996	-.0081765
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Panel B: Comparative Statistics for Bond Funds During 2008-2009

Bond Funds								
	2008Q1	**2008Q2**	**2008Q3**	**2008Q4**	**2009Q1**	**2009Q2**	**2009Q3**	**2009Q4**
Mean of Alpha5F								
CDS users	-.0418206	-.0016449	-.0700393	-.0590247	-.0122679	.0607305	.0827546	.0422017
CDS nonusers	-.04877	.00185	-.0444415	-.0457651	.0340249	.0517659	.0930016	.0209592
Diff	-0.0069494	0.0034949	0.0255978	0.0132596	0.0462928	-0.0089646	0.010247	-0.0212425
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 3.4: The Determinants of CDS Use

The table presents factors that are correlated with funds' decisions to trade CDS with a probit setting. The regressions are estimated on fund-date level yet some of the independent variables are available of different frequency thus are represented by repeated values in the data set. The dependent variable is a dummy variable that equals to one if at least one CDS position is observed for the fund quarter. CDSP is the average CDS spread obtained over Datastream is on basis point terms. BAA10Y is the 10-year BAA rated corporate bond spread in basis points. Expense ratio and turnover ratio are on percentage terms. 5-factors alpha is defined as in Section 3.3 and is annualized. HY is an indicative dummy variable that equals to one for high yield funds as defined by Fang, Kempf and Trapp (2014). CDS and bond spreads at t-1 are the respective spreads on the last day of the previous quarter. Time t-1 alpha is the estimated alpha for the last month of the previous quarter. In each cell the reported are marginal effects and z statistics. All standard errors are clustered at fund level. In columns (2), (3) and (4) time dummies are included. Marginal effects of coefficients are reported.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln(TNA)	0.0370***	0.0379***	0.0351***	0.0355***	0.0368***	0.0369***	0.0372***
	(7.43)	(7.46)	(7.22)	(7.15)	(7.35)	(7.35)	(7.36)
Expense	0.112***	0.112***	0.128***	0.0812***	0.115***	0.0980***	0.0942***
	(5.32)	(5.29)	(3.69)	(4.09)	(5.39)	(4.99)	(4.86)
Turnover	0.0211***	0.0209***	0.0222***	0.0232***	0.0210***	0.0206***	0.0204***
	(5.25)	(5.19)	(5.51)	(5.66)	(5.23)	(5.45)	(5.47)
Alpha5F			0.0349***	0.0511***	0.0404*	0.0374**	0.0770***
			(3.02)	(2.67)	(1.83)	(2.18)	(3.52)
CDSP	0.000708***	0.000204*	0.000459**		0.000885***		
	(4.12)	(1.70)	(2.05)		(4.33)		
BAA10Y				0.0000386**		0.000136***	0.000285***
				(1.99)		(4.85)	(6.00)
HY			0.0223	0.0000779			
			(0.66)	(0.02)			
CRSP(T-1)					-0.000269		
					(-1.16)		
BAA10Y(T-1)						-0.0000821**	
						(-2.79)	
Alpha5F(T-1)					0.00534	0.0337*	
					(0.27)	(1.80)	
Post08Q3							0.0122
							(0.72)
Post08Q3 $\times$ BAA10Y							-0.000178***
							(-3.58)
Observations	2322760	2322760	2322615	2767275	1711215	1962634	2767275
Pseudo R^2	0.0825	0.0853	0.0841	0.0836	0.0851	0.0830	0.0828
Time Fe	No	Yes	Yes	Yes	No	No	No
Clustered Std	Fund	Fund	Fund	Fund	Fund	Fund	Fund

Marginal effects; z statistics in parentheses

(d) for discrete change of dummy variable from 0 to 1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: CDS Use and Fund Performance, Tail Risk, and Tracking Error

The table evaluates fund performance, tail risk and tracking error in a pooled OLS setting. The dependent variables are fund performance and risk measures. 5-factors alpha is defined as in Section 3.3 and is annualized. Tracking errors are computed from with 5-factors model. Tail risk definition follows Kelly and Jiang (2014) and is standardized. CDS is a dummy that equals to one if at least one CDS position is observed for the fund quarter. CDSP is the average CDS spread obtained over Datastream is on basis point terms. BAA10Y is the 10-year BAA rated corporate bond spread in basis points. Crisis equals to one for the period 2007Q3 to 2009Q2. HY is an indicative dummy variable that equals to one for high yield funds as defined by Fang, Kempf and Trapp (2014). In each cell the reported are coefficients and t statistics. All standard errors are clustered at fund level. Fund fixed effects are included in all specifications.

	(1) Alpha5F	(2) Alpha5F	(3) Alpha5F	(4) Alpha5F	(5) TE	(6) TE	(7) TR	(8) TR
Ln(TNA)	-0.00303**	-0.00613***	-0.0202***	-0.0148***	-0.0110***	-0.0115***	-0.0394***	-0.0381***
	(-2.37)	(-4.50)	(-9.60)	(-9.96)	(-3.39)	(-3.52)	(-3.41)	(-3.29)
Expense	0.00111	0.0143**	0.0300***	0.0218***	0.0191	0.0199	-0.0285	-0.0299
	(0.27)	(2.53)	(4.18)	(4.11)	(1.17)	(1.23)	(-0.48)	(-0.50)
Turnover	-0.000368	0.00150	0.00109	0.000212	0.00405*	0.00377*	-0.0177**	-0.0170**
	(-0.57)	(1.35)	(0.92)	(0.22)	(1.77)	(1.65)	(-2.40)	(-2.29)
CDS	0.00466*	0.0199***	0.0114**	0.00596	0.0224***	0.0254***	0.0319**	0.0295**
	(1.90)	(5.68)	(2.04)	(0.99)	(4.36)	(4.46)	(2.23)	(2.32)
Crisis		-0.0725***	-0.0641***	0.00232	0.240***	0.245***	-0.0178	-0.0280**
		(-33.95)	(-20.49)	(0.77)	(63.06)	(60.18)	(-1.34)	(-2.02)
CDSP			0.000368***					
			(51.45)					
CDS × Crisis		-0.0286***	-0.0193***	-0.0268***	0.00455	0.00824	0.0635**	0.0547*
		(-5.22)	(-5.73)	(-4.67)	(0.51)	(0.94)	(2.26)	(1.91)
CDS × CDSP			0.000325***					
			(4.39)					
Crisis × CDSP			-0.000284***					
			(-27.98)					
CDS × Crisis × CDSP			-0.000541***					
			(-4.59)					
BAA10Y				0.000321***				
				(47.69)				
CDS × BAA10Y				0.000242***				
				(5.38)				
Crisis × BAA10Y				-0.000317***				
				(-28.65)				
CDS × Crisis × BAA10Y				-0.000412***				
				(-6.66)				
HY						-0.0226		-0.0269
						(-0.76)		(-0.24)
CDS × HY						-0.0120		0.00986
						(-0.92)		(0.19)
Crisis × HY						-0.0368***		0.0843***
						(-4.49)		(2.74)
CDS × Crisis × HY						-0.0201		-0.0767
						(-0.91)		(-1.18)
Observations	2767275	2767275	2322615	2767275	2767255	2767255	2767432	2767432
Adjusted R^2	0.314	0.095	0.321	0.207	0.304	0.305	0.002	0.002
Fund Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fe	Yes	No	No	No	No	No	No	No
Clustered Std	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: CDS Use and Fund Risk

The table evaluates the effect of CDS use on various fund risk measures of Adam and Guettler (2015) in a pooled OLS setting. The dependent variables are fund risk measures as defined in Section 3.3. CDS is a dummy that equals to one if at least one CDS position is observed for the fund quarter. Crisis equals to one for the period 2007Q3 to 2009Q2. In each cell the reported are coefficients and t statistics. All standard errors are clustered at fund level. Included fund level controls are fund TNA, expense ratio and turnover ratio. Fund fixed effects are included in all specifications.

	(1) BETA	(2) SD	(3) KURTOSIS	(4) SKEWNESS	(5) DOWNBETA	(6) UPBETA
CDS	-0.0119	0.000118***	-0.139*	-0.0627**	-0.0146	-0.00298
	(-1.08)	(4.31)	(-1.96)	(-2.50)	(-1.23)	(-0.25)
Crisis	-0.0241***	0.00121***	-0.788***	-0.191***	-0.0211***	-0.0654***
	(-4.82)	(62.47)	(-18.22)	(-13.73)	(-3.58)	(-14.67)
CDS $\times$ Crisis	0.0447***	0.000164***	-0.186**	-0.0729**	0.0601***	0.0103
	(4.13)	(3.83)	(-2.16)	(-2.32)	(4.29)	(0.84)
Observations	2767275	2767275	2767209	2767209	2767272	2767275
Adjusted R^2	0.012	0.304	0.034	0.021	0.005	0.008
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fe	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Std	Fund	Fund	Fund	Fund	Fund	Fund

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: CDS Use and Fund Outcomes: An IV Approach

The table evaluates the effect of CDS use on various fund outcome variables. The dependent variables are fund performance and risk measures as defined in Section 3.3. CDS is a predicted variable results from the first stage regression. Crisis equals to one for the period 2007Q3 to 2009Q2. In the first stage we regress a CDS dummy on other funds' use of CDS dummy, as well as other independent variables and fund controls. The fitted value of CDS is plugged into the second stage. In each cell the reported are coefficients and t statistics. All standard errors are clustered at fund level. Included fund level controls are fund TNA, expense ratio and turnover ratio. Fund fixed effects are included in all specifications in both the first and the second stage.

	(1) Alpha5F	(2) Alpha4F	(3) Alpha3F	(4) Alpha1F	(5) RET	(6) SD	(7) TE	(8) TR
CDS	0.108***	0.0318***	0.139***	0.120***	0.000532***	0.000516***	0.116***	0.181*
	(5.77)	(3.14)	(6.56)	(6.71)	(6.75)	(3.75)	(4.32)	(1.79)
Crisis	-0.0696***	-0.0342***	-0.0591***	-0.0756***	-0.000251***	0.00123***	0.247***	-0.00302
	(-28.98)	(-18.86)	(-19.22)	(-21.83)	(-17.14)	(62.52)	(62.54)	(-0.22)
CDS × Crisis	-0.0733***	-0.0233***	-0.109***	-0.110***	-0.000462***	-0.0000298	-0.0422**	-0.0150
	(-6.72)	(-3.46)	(-7.86)	(-8.30)	(-7.97)	(-0.36)	(-2.57)	(-0.26)
Observations	2614886	2614886	2614886	2614886	2613672	2614886	2614872	2615000
Adjusted R^2	0.069	0.043	0.030	0.084	0.001	0.304	0.299	-0.001
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Std	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund
First Stage	Kleibergen-Paap rk LM statistic: 97.869; $p = 0.0000$							
First Stage	Cragg-Donald Wald F statistic: $6.4e + 04$ Kleibergen-Paap rk Wald F statistic: 125.308							
First Stage	Hansen J statistic: 0.000							

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: Fund Performance and Risk Following Sudden CDS Closures: The DiD Analysis

The table evaluate the treatment effects of sudden CDS closures on fund performance and risk. The dependent variables are fund performance and risk measures as defined in Section 3.3. DiD_1 and DiD_2 are difference in differences estimators for period 1 and period 2 respectively. Period 1 includes 2008Q4 and 2009Q1, while period 2 refers to the periods afterwards until 2014. Post_1 and Post_2 are dummies variables that equal to one for these two periods respectively. Treated is an indicator for the treated group. The regressions are based on the sample of the treated and control funds, as defined in Section 3.5.2 and Section 3.5.3. In each regression fund level controls fund size, expense ratio and turnover ratio are included. In each cell the reported are coefficients and t statistics. All standard errors are clustered at fund level.

	(1) Alpha5F	(2) Alpha4F	(3) Alpha3F	(4) Alpha1F	(5) RET	(6) SD	(7) TE	(8) TR	(9) FLOW	(10) BETA
DiD_1	0.0249	0.0254	-0.0241	-0.0208	-0.000231**	0.000411	0.136***	0.129	-0.00779	-0.0714
	(1.20)	(1.40)	(-1.12)	(-1.10)	(-2.23)	(1.56)	(3.07)	(0.84)	(-0.82)	(-1.51)
DiD_2	-0.0212**	-0.0244***	-0.0101	-0.00349	-0.000229***	-0.000306***	-0.00326	-0.0559	0.000525	-0.106**
	(-2.27)	(-3.51)	(-1.10)	(-0.28)	(-2.85)	(-3.20)	(-0.22)	(-0.60)	(0.11)	(-2.37)
POST_1	-0.0580***	-0.0196***	0.0100	-0.0820***	-0.000293***	0.00210***	0.366***	0.0336	-0.0148***	0.00295
	(-6.56)	(-2.63)	(1.01)	(-7.95)	(-6.28)	(13.07)	(16.45)	(0.45)	(-2.97)	(0.15)
POST_2	0.0987***	0.0331***	0.115***	0.0848***	0.000276***	-0.000187***	-0.0349***	-0.0804*	-0.00129	-0.0791***
	(19.09)	(11.43)	(18.82)	(10.89)	(9.60)	(-3.72)	(-4.10)	(-1.73)	(-0.45)	(-3.14)
Treated	0.0000616	-0.000656	-0.00580	-0.00662	-0.0000353	0.000182	0.0602***	0.122	0.00245	0.0175
	(0.01)	(-0.17)	(-1.26)	(-1.22)	(-1.54)	(1.60)	(2.97)	(1.19)	(0.52)	(0.26)
Observations	181801	181801	181801	181801	181788	181801	181801	181802	181802	181801
Adjusted R^2	0.170	0.081	0.172	0.172	0.006	0.284	0.277	0.011	0.005	0.178
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Std	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: AARE of the Treated and Control Funds

The table reports the mean of average abnormal return (AARE) for treated funds and control funds. In the first step abnormal returns in each fund day are averaged within treated and control groups. In the second step we test whether the mean of the two AARE time series are statistically different in various time windows post event. Panel A is dedicated to AARE computed by 5-factors alpha model, while in panel B we use a self-defined index constructed from mutual fund returns in each fund category as the benchmark return. The event date is 15th September 2018 when Lehman declared bankruptcy. Treated funds are those 31 funds with significant Lehman CDS exposure and meet all other treated definition as in Section 3.5.2. Control funds are those that have closest propensity scores with the treated funds using 5 nearest neighbour propensity score matching technique as described in Section 3.5.3.

Panel A: 5-Factors model AARE

	Mean of Treated	Mean of Control	Diff	p
[0,20]	-.0037289	-.0043178	.000589	0.0617
(20,40]	-.0010235	-.0008006	-.0002229	0.4913
(40,60]	-.0022391	-.0020129	-.0002262	0.3465
(60,120]	-.0002606	.0001386	-.0003992	0.0013

Panel B: Defined Index model AARE

	Mean of Treated	Mean of Control	Diff	p
[0,20]	-.003766	-.0034036	-.0003624	0.2867
(20,40]	-.0005019	-.0002331	-.0002688	0.3928
(40,60]	-.0021925	-.0013562	-.0008363	0.0123
(60,120]	-.0000254	.0004119	-.0004373	0.0293

Table 3.10: Fund Performance and Risk Following CDS Reconstruction

The table evaluate the effects of CDS reconstruction on fund performance and risk. The sample is the original treated fund quarters. The dependent variables are fund performance and risk measures as defined in Section 3.3. DiD_1 and DiD_2 are difference in differences estimators for period 1 and period 2 respectively. Period 1 includes 2008Q4 and 2009Q1, while period 2 refers to the periods afterwards until 2014. Post_1 and Post_2 are dummies variables that equal to one for these two periods respectively. Rebuild is an indicator for the funds that rebuild Lehman contracted CDS positions within the treated group. In each regression fund level controls fund size, expense ratio and turnover ratio are included. In each cell the reported are coefficients and t statistics. All standard errors are clustered at fund level.

	(1) Alpha5F	(2) Alpha4F	(3) Alpha3F	(4) Alpha1F	(5) RET	(6) SD	(7) TE	(8) TR	(9) FLOW	(10) BETA
Post_1 × Rebuild	-0.0513	-0.0483	-0.0480	-0.0495	-0.000181	-0.000256	-0.0163	-0.114	-0.0388*	-0.140
	(-0.74)	(-1.10)	(-0.75)	(-1.26)	(-0.74)	(-0.52)	(-0.19)	(-0.31)	(-1.92)	(-0.94)
Post_2 × Rebuild	0.0431**	0.0385*	0.0214	0.000639	0.0000287	-0.000161	-0.00438	-0.264*	0.00943	0.136*
	(2.59)	(1.86)	(1.17)	(0.02)	(0.34)	(-1.13)	(-0.17)	(-1.98)	(0.77)	(1.82)
Post_1	0.0167	-0.0599***	-0.0320	-0.126***	-0.000500***	0.00281***	0.498***	0.182	-0.0178**	-0.0488
	(0.82)	(-3.15)	(-1.50)	(-6.61)	(-4.89)	(12.14)	(11.98)	(1.23)	(-2.10)	(-1.08)
Post_2	0.105***	0.0383***	0.136***	0.117***	0.000395***	-0.000192**	-0.0409***	-0.103	-0.00300	-0.207***
	(12.92)	(6.51)	(17.65)	(10.07)	(9.38)	(-2.06)	(-3.08)	(-1.09)	(-0.66)	(-4.74)
Rebuild	-0.0291***	-0.0265***	-0.0202**	-0.0189	-0.0000759	0.00000818	0.0130	0.206	-0.0138**	0.0577
	(-3.51)	(-3.03)	(-2.73)	(-1.33)	(-1.68)	(0.03)	(0.29)	(0.91)	(-2.08)	(0.38)
Observations	56084	56084	56084	56084	56080	56084	56084	56085	56085	56084
Adjusted R^2	0.233	0.207	0.248	0.275	0.009	0.355	0.327	0.026	0.014	0.281
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Std	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.11: Fund Performance and Risk Following CDS Reconstruction: Randomized Rebuilding Funds

The table evaluate the effects of CDS reconstruction on fund performance and risk as a placebo to Table 3.10. We randomize the 4 funds that rebuilt within the treated sample. The sample is the original treated fund quarters. The dependent variables are fund performance and risk measures as defined in Section 3.3. DiD_1 and DiD_2 are difference in differences estimators for period 1 and period 2 respectively. Period 1 includes 2008Q4 and 2009Q1, while period 2 refers to the periods afterwards until 2014. Post_1 and Post_2 are dummies variables that equal to one for these two periods respectively. Rebuild is a randomized indicator for the funds that rebuild Lehman contracted CDS positions within the treated group. In each regression fund level controls fund size, expense ratio and turnover ratio are included. In each cell the reported are coefficients and t statistics. All standard errors are clustered at fund level.

	(1) Alpha5F	(2) Alpha4F	(3) Alpha3F	(4) Alpha1F	(5) RET	(6) SD	(7) TE	(8) TR	(9) FLOW	(10) BETA
Post_1 × Rebuild_Random	-0.0504	-0.0210	-0.0490	-0.0106	-0.000162	0.000191	-0.0920	0.476	-0.00360	-0.195
	(-1.02)	(-0.63)	(-0.99)	(-0.28)	(-0.74)	(0.31)	(-1.14)	(1.50)	(-0.14)	(-1.30)
Post_2 × Rebuild_Random	-0.0136	0.0106	0.00177	0.0290	0.0000620	0.000108	-0.0241	0.0812	0.0173	-0.102
	(-0.53)	(0.38)	(0.07)	(0.73)	(0.44)	(0.43)	(-0.81)	(0.41)	(1.30)	(-1.01)
Post_1	0.0170	-0.0637***	-0.0313	-0.131***	-0.000499***	0.00275***	0.511***	0.0883	-0.0228**	-0.0440
	(0.78)	(-3.21)	(-1.38)	(-6.76)	(-4.84)	(12.29)	(12.50)	(0.60)	(-2.66)	(-0.97)
Post_2	0.115***	0.0431***	0.140***	0.112***	0.000390***	-0.000222**	-0.0344***	-0.151	-0.00413	-0.163***
	(14.69)	(7.26)	(21.13)	(11.20)	(11.18)	(-2.68)	(-2.88)	(-1.68)	(-0.98)	(-3.84)
Rebuild_Random	-0.00218	0.000686	-0.00259	-0.0117	-0.0000328	-0.000407	-0.0718	-0.294	-0.00609	-0.0656
	(-0.15)	(0.04)	(-0.19)	(-0.71)	(-0.50)	(-1.57)	(-1.30)	(-1.54)	(-0.48)	(-0.41)
Observations	56084	56084	56084	56084	56080	56084	56084	56085	56085	56084
Adjusted R^2	0.228	0.192	0.246	0.273	0.009	0.362	0.347	0.032	0.010	0.281
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Std	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.12: Mutual Funds' CDS Counterparties 2006-2014

The table reports the CDS counterparties that mutual funds contracted with during the period 2006 to 2010 as in their NQ, NCSR, NCSRS reports to the SEC. A number of counterparties with minimum number of positions observable are not included. The fraction is expressed in percentages.

Counterparty	% of CDS Positions
ABN AMRO Bank	0.0354
Bank Of America	5.6763
Barclay's	6.8692
Bear Stearns	2.1109
BNP Paribas	1.4146
Citi	7.9911
Credit Suisse First Boston	9.7029
Deutsche Bank	12.7916
Goldman Sachs	12.2350
HSBC	0.9823
JPMorgan Chase	9.1264
Lehman Brothers	7.0865
Merrill Lynch	5.2173
Morgan Stanley	9.2306
Royal Bank of Scotland	5.5299
UBS AG	3.7029
Wachovia Bank	0.0953
Societe Generale	0.1042

Table 3.13: Fund Performance and Risk Following Sudden CDS Closures: Randomized Treated Sample

The table evaluates fund performance and risk for a randomized sample of 31 funds following the Lehman collapse. The dependent variables are fund performance and risk measures as defined in Section 3.3. Period 1 includes 2008Q4 and 2009Q1, while period 2 refers to the periods afterwards until 2014. Post_1 and Post_2 are dummies variables that equal to one for these two periods respectively. Treated_Random is an indicator for the randomized treated group. The regressions are based on the sample of the treated and control funds, as defined in Section 3.5.2 and Section 3.5.3. In each regression fund level controls fund size, expense ratio and turnover ratio are included. In each cell the reported are coefficients and t statistics. All standard errors are clustered at fund level.

	(1) Alpha5F	(2) Alpha4F	(3) Alpha3F	(4) Alpha1F	(5) RET	(6) SD	(7) TE	(8) TR	(9) FLOW	(10) BETA
Post_1 × Treated_Random	-0.00126	-0.00380	-0.00810	-0.0177	-0.0000417	0.000142	-0.00657	-0.0156	-0.0127*	-0.00691
	(-0.09)	(-0.27)	(-0.54)	(-0.95)	(-0.52)	(0.68)	(-0.22)	(-0.14)	(-1.72)	(-0.22)
Post_2 × Treated_Random	0.00117	-0.00457	0.00113	0.00225	0.0000115	0.0000254	0.00255	0.0401	-0.00633	-0.00231
	(0.16)	(-0.63)	(0.12)	(0.17)	(0.25)	(0.23)	(0.16)	(0.47)	(-1.18)	(-0.05)
Post_1	-0.0639***	0.00893	-0.0340***	-0.0320***	-0.000137***	0.00197***	0.430***	0.0126	-0.00345	-0.0424***
	(-9.63)	(1.36)	(-4.74)	(-3.72)	(-3.63)	(21.08)	(24.98)	(0.26)	(-0.96)	(-3.09)
Post_2	0.0859***	0.0414***	0.0949***	0.0708***	0.000198***	-0.000134**	-0.0167	-0.0340	0.00243	-0.0940***
	(21.11)	(11.64)	(20.53)	(13.00)	(9.89)	(-2.17)	(-1.49)	(-0.69)	(1.03)	(-5.00)
Treated_Random	0.000605	0.000141	0.0000341	0.000448	0.00000178	0.0000609	-0.0126	0.0190	0.00222	0.0212
	(0.15)	(0.04)	(0.01)	(0.11)	(0.11)	(0.46)	(-0.52)	(0.18)	(0.56)	(0.37)
Observations	322964	322964	322964	322964	322920	322964	322964	322965	322965	322964
Adjusted R^2	0.144	0.073	0.141	0.126	0.002	0.223	0.248	0.038	0.002	0.132
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Std	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund

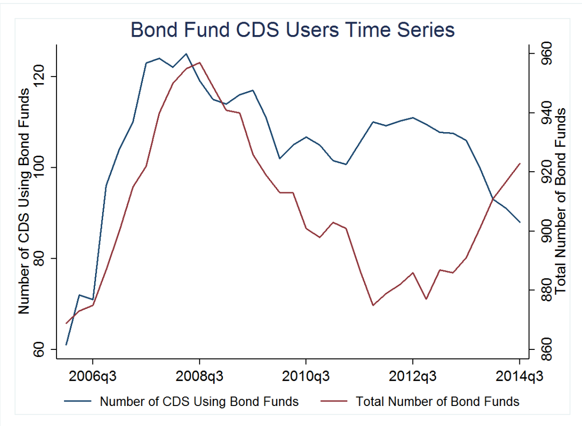
t statistics in parentheses

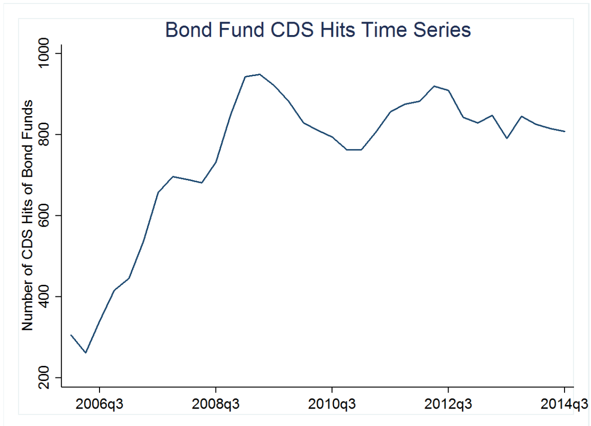
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3.1: Time Series of the Number of CDS Using Funds and CDS Hits

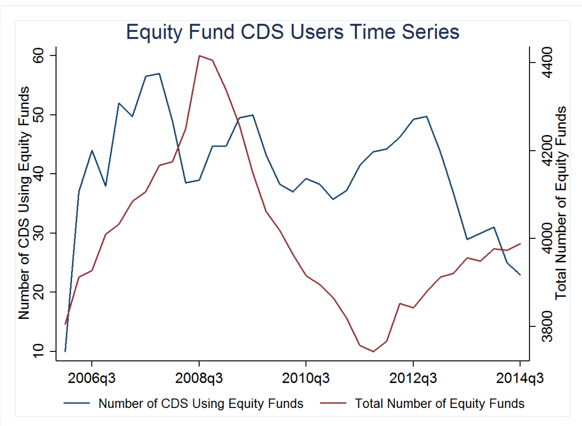
The graph depicts the time trend of the number of CDS using funds and the number of CDS positions for fixed income funds and equity funds respectively, and contrast them with the total number of funds in each category. The time frame is from 2006 to 2014 that covers our entire sample period. Fund type is as defined by the first letter of the CRSP objective code, and cross checked with Lipper, Strategic Insight and Wberger objective codes. For the first graph in each panel, the two Y variables are depicted over two Y axis, with different scaling. The total number of funds refers to the number of funds in our final sample that results from the match of the CRSP universe through MFLinks with the Edgar Universe. A fund is defined as a CDS using fund if there exists at least one CDS position in the table environment of their NQ, NCSR, or NCSRS filings in each respective quarter. A CDS hit should be within the table environment that details funds' CDS holdings and the start as well as the end of the position can be reasonably judged from the html codes.

Panel A: CDS using time series for fixed income mutual funds





Panel B: CDS using time series for equity mutual funds



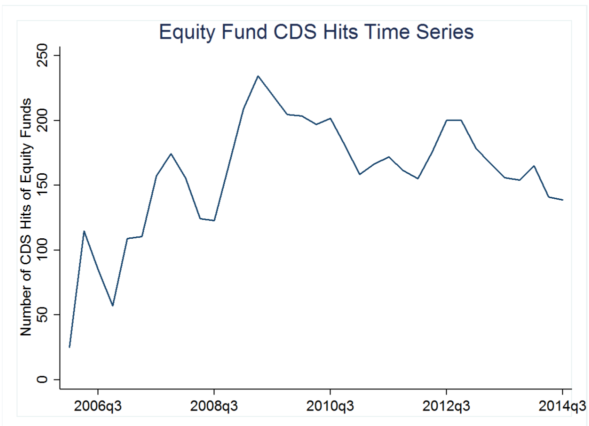
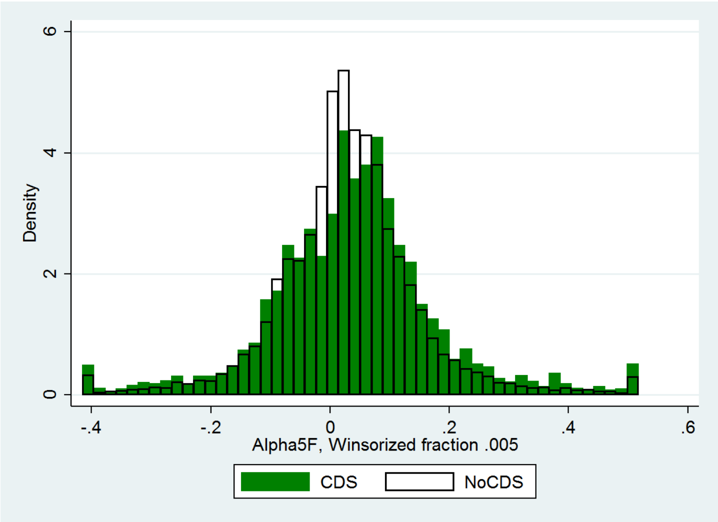


Figure 3.2: The Distribution of 5-Factors Alpha

The graph shows the distribution of 5-factors alpha for CDS users (green bar) and CDS nonusers (black edged empty box) in two density histograms. Panel A is built upon data across all sample periods, and panel B focuses on the comparison in 2008. CDS users are funds that hold at least one CDS position at the fund quarter. The alpha are annualized and are as defined in Section 3.3.

Panel A: Entire Sample Period



Panel B: Year 2008

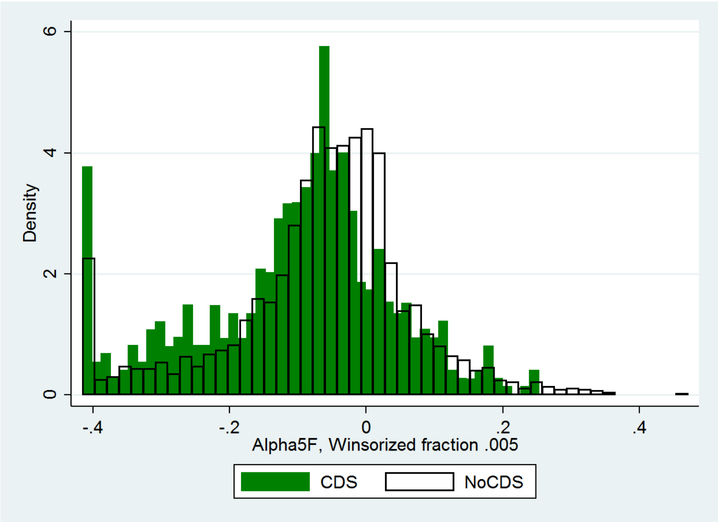
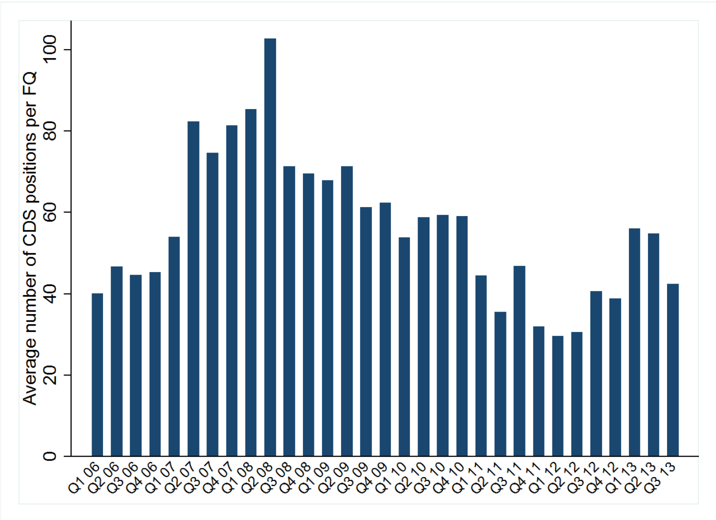


Figure 3.3: The Average Number of CDS Positions Per Fund Quarter: A Time Series Comparison

The graph shows the average number of CDS positions per fund quarter separately for treated funds and all other CDS using funds over the sample period. Panel A is dedicated for the treated funds group, and panel B focuses on other CDS using funds. Treated funds are defined as in Section 3.5.2.

Panel A: Treated Funds



Panel B: All other CDS Using Funds

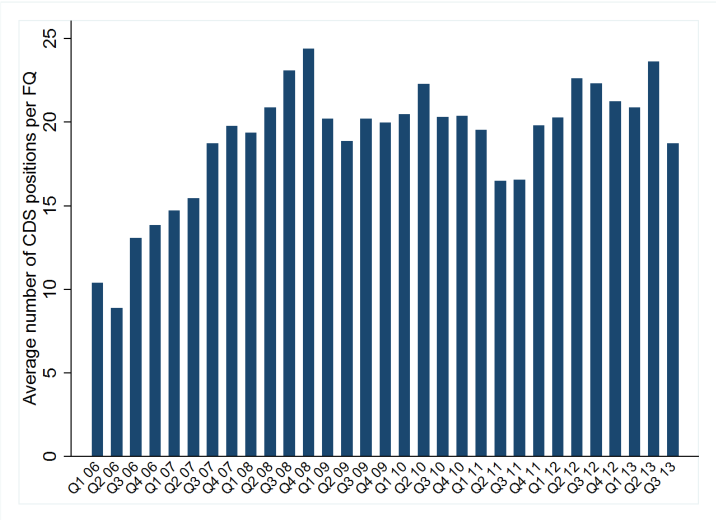
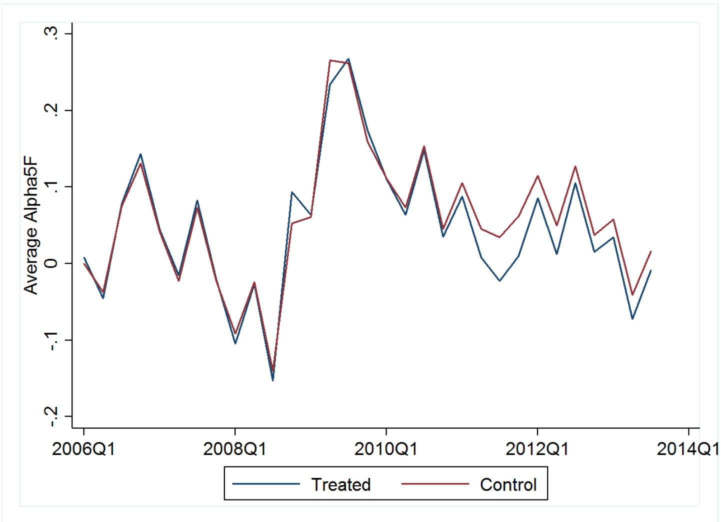


Figure 3.4: Average 5 Factors Alpha and Standard Deviation for the Treated and Control Funds: A Time Series Comparison

We present here the trend of 5-factors alpha and fund return standard deviation before and after the event for the treated funds and control funds separately. 5-factors alpha and standard deviation are computed as defined in Section 3.3. The event date is 15th September 2018 when Lehman declared bankruptcy. Treated funds are those 31 funds with significant Lehman CDS exposure and meet all other treated definition as in Section 3.5.2. Control funds are those that have closest propensity scores with the treated funds using 5 nearest neighbour propensity score matching technique as described in Section 3.5.3.

Panel A: 5 Factors Alpha



Panel B: Return Standard Deviation

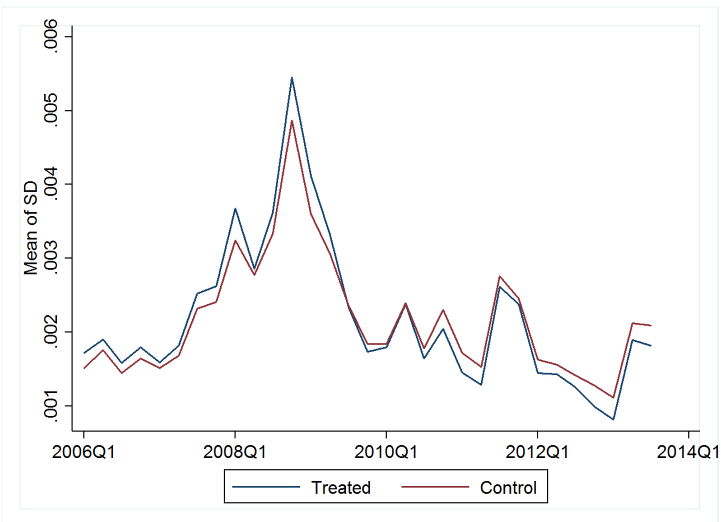
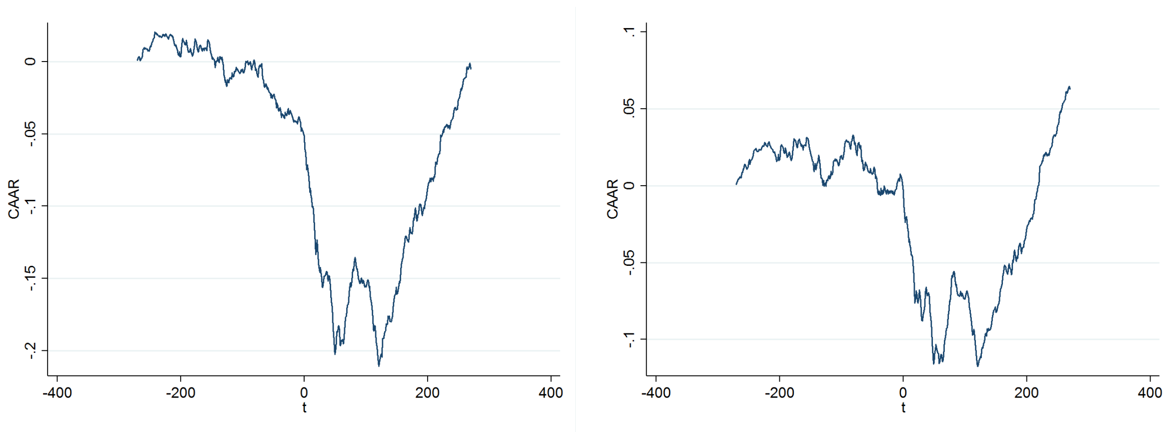


Figure 3.5: Time Series of CAAR for the Treated and Their Control Funds

The graph plots the time series of estimated CAAR for the treated funds and control funds separately. In the two graphs on the left 5-factors model is employed, while in the other two graphs a self-defined index constructed from mutual fund returns in each fund category is used as benchmark return. Vertical comparison between the treated and control groups is recommended. The event date is 15th September 2018 when Lehman declared bankruptcy. Treated funds are those 31 funds with significant Lehman CDS exposure and meet all other treated definition as in Section 3.5.2. Control funds are those that have closest propensity scores with the treated funds using 5 nearest neighbour propensity score matching technique as described in Section 3.5.3.

Panel A: CAAR Time Series Treated Funds (Left: 5F; Right: Defined Index)



Panel B: CAAR Time Series Control Funds (Left: 5F; Right: Defined Index)

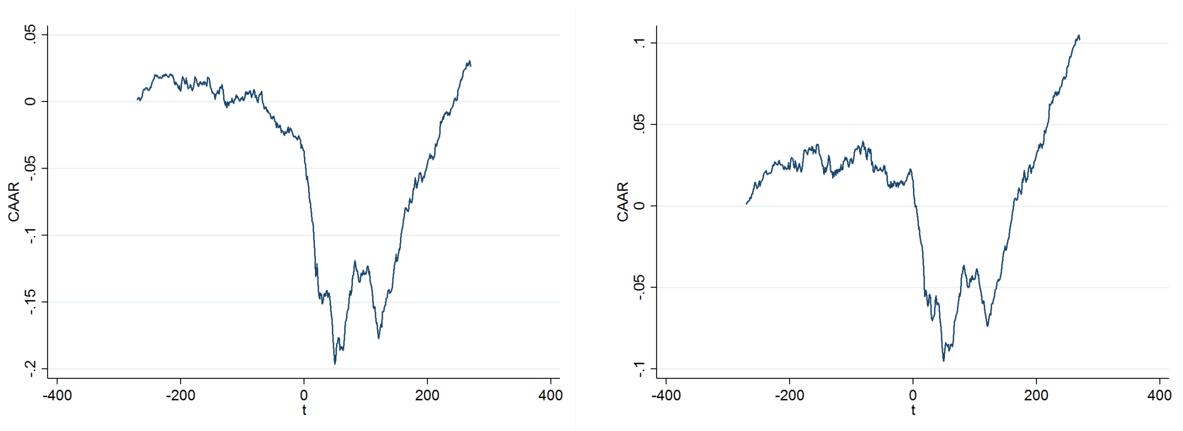
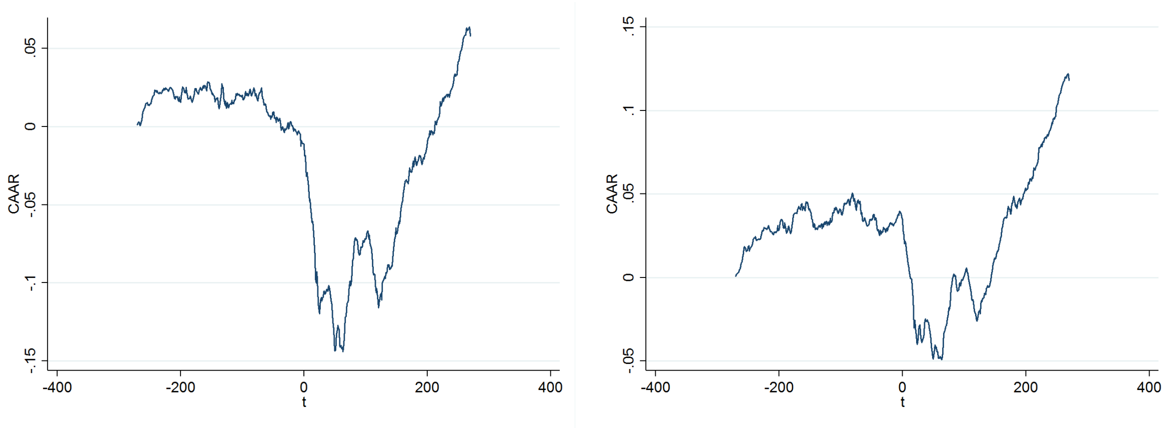


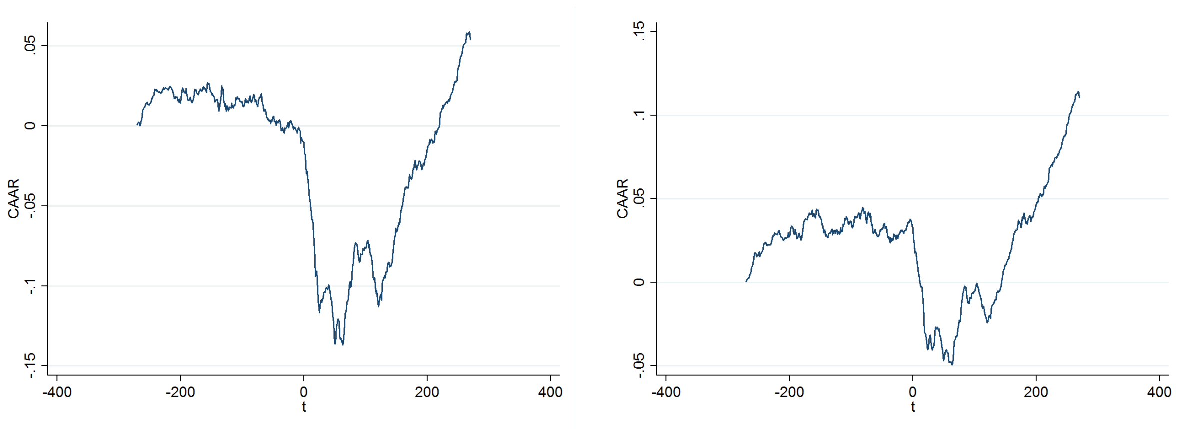
Figure 3.6: Time Series of CAAR for Randomized Treated and Their Control Funds

The graph plots the time series of estimated CAAR for the randomized treated funds and control funds separately. In the two graphs on the left 5-factors model is employed, while in the other two graphs a self-defined index constructed from mutual fund returns in each fund category is used as benchmark return. Vertical comparison between the treated and control groups is recommended. The event date is 15th September 2018 when Lehman declared bankruptcy. Treated funds are 31 funds randomly selected from the fund universe. Control funds are those that have closest propensity scores with the randomized treated funds using 5 nearest neighbour propensity score matching technique as described in Section 3.5.3.

Panel A: CAAR Time Series Treated Funds (Left: 5F; Right: Defined Index)



Panel B: CAAR Time Series Control Funds (Left: 5F; Right: Defined Index)



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Selbständigkeitserklärung

Thomas Verchow hat mich bei der Erhebung der CDS-Daten für das 3. Kapitel freundlich unterstützt.

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtung meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

Berlin, den 27.03.2018 Li Ma